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A review and comparative analysis of maximum power point tracking control algorithms for wind energy conversion systems

Yakob Kiros Teklehaimanot[1] · **Francis Kayode Akingbade**[1] · **Brendan Chijioke Ubochi**[1] · **Thomas Olabode Ale**[1]

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Abstract
In the current era, renewable energy has emerged as a vital alternative to fossil fuels, driven by the repercussions of global warming and the depleting supply of fossil fuels. Among these alternative energies, wind energy is particularly noteworthy due to its minimal greenhouse gas emissions, cost-effectiveness, and widespread availability. Nonetheless, achieving efficient extraction of wind energy requires precise control of wind turbine operations to optimize power generation. This involves the utilization of different maximum power point tracking (MPPT) algorithms. This review paper extensively examines a variety of MPPT algorithms, classifying them into four main categories: indirect power control (IPC) algorithm, direct power control (DPC) algorithm, hybrid algorithm, and intelligent algorithm control techniques. The review explores the performance of conventional IPC and DPC algorithms, discussing and comparing them with modified conventional methods. Additionally, the hybrid approach, combining multiple MPPT algorithms to leverage benefits while mitigating drawbacks, is examined. Intelligent MPPT algorithms are discussed both independently and in hybrid configurations. The paper introduces a hybrid fractional-order intelligent MPPT algorithm, offering a detailed discussion and comparison with other intelligent algorithms. A meticulous comparison is conducted based on key parameters such as adaptability, computational complexity, efficiency, oscillation, overall expense, robustness, speed of convergence, storage, time response, wind speed measurement, and wind turbine characteristics. Acknowledging the exponential growth in wind energy systems and their increasing significance, this review paper aims to be an indispensable and technically advanced reference for future studies in the dynamic domain of MPPT algorithm control techniques for wind energy systems.

Keywords Fractional-order · MPPT algorithms · Renewable energy · Wind energy conversion systems · Wind turbine

1 Introduction

The imperative shift toward renewable energy in the electric power generation sector is underscored by the gradual depletion of fossil fuels and the escalating threat of global warming. Renewable energy plays a pivotal role in addressing one of the most pressing challenges of our time: global warming. As societies worldwide confront the escalating threats posed by climate change, the transition to renewable energy sources emerges as a critical pathway toward sustainability and environmental preservation. At its core, renewable energy encompasses energy derived from naturally replenishing sources, such as sunlight, wind, water, and geothermal heat. Unlike fossil fuels, which emit greenhouse gases upon combustion, renewable energy technologies offer cleaner and more sustainable alternatives that significantly reduce carbon emissions [1, 2]. Among these renewable energy sources, wind energy stands out as a particularly promising solution for mitigating global warming. Wind power harnesses the kinetic energy generated by the natural movement of air masses, converting it into electricity through turbines. This process is both environmental friendly and sustainable, as it

Francis Kayode Akingbade, Brendan Chijioke Ubochi and Thomas Olabode Ale contributed equally to this work.

✉ Yakob Kiros Teklehaimanot
teklehaimanotyk@futa.edu.ng

Francis Kayode Akingbade
kfakingbade@futa.edu.ng

Brendan Chijioke Ubochi
bcubochi@futa.edu.ng

Thomas Olabode Ale
toale@futa.edu.ng

1 Electrical and Electronics Engineering, Federal University of Technology Akure (FUTA), FUTA Main Road, Akure 34011, Ondo, Nigeria

produces no greenhouse gas emissions or air pollutants during electricity generation. By displacing conventional fossil fuel-based power generation, wind energy plays a crucial role in reducing the carbon footprint of electricity production and mitigating the adverse impacts of climate change. The importance of wind energy in combating global warming lies in its ability to provide a scalable and cost-effective solution for transitioning toward a low-carbon energy future. Wind power offers several key advantages over traditional energy sources: abundant resource, zero emissions, cost competitiveness, job creation and economic growth, and grid integration and energy storage [3, 4].

The production of wind energy has experienced significant growth in the past two decades, propelled by the increasing demand for electrical energy. During the 21st World Wind Energy Conference (WWEC2023) held in Hobart, Australia, on November 7, 2023, the World Wind Energy Association (WWEA) unveiled its Semi-annual Report. This report offers an in-depth summary of the present worldwide state of the wind energy sector [5]. The report, based on a survey conducted among WWEA's member associations worldwide, offers estimates of new wind power installations in the first 6 months of 2023 and predicts figures for the year's end. As of the report's publication, there has been a remarkable 38% increase in new installations in the first half of 2023 compared to 2022, with an impressive addition of 100 Gigawatts between June 2022 and June 2023, bringing the total to 976 GW. The annual growth rate is reported at 11.4%, and at least an additional 100 Gigawatt of new installations is anticipated by the end of 2023, aiming for a total capacity of 1 million Megawatts [5–7]. Figure 1 illustrates the global installed wind power capacity in Megawatts on a yearly basis, projecting a value of approximately 1.7 million Megawatts by 2030. According to calculations from [8], the wind turbine energy sector is anticipated to contribute around 795.311 billion dollars in the year 2030. Figure 2 depicts the annual addition of wind power from 2011 to 2023.

The significant expansion highlighted here emphasizes the growing importance of the wind energy market. The increasing adoption of wind energy not only meets the pressing demand for sustainable energy sources, but also indicates a favorable shift toward a more environmentally aware and robust energy landscape. As the world steadily moves toward cleaner energy options, the role of wind energy in the global power generation mix is anticipated to become even more substantial in the future [5].

Wind turbine systems, ranging from simple designs to more intricate configurations, face inherent challenges associated with climate fluctuations and environmental factors. This emphasizes the crucial role of integrated control systems, which are instrumental in ensuring the effective functioning of wind turbines. These systems play an essential role in providing stability for grid integration and optimizing the utilization of wind energy for maximum power generation [9]. The turbine rotor, gearbox, generator, transformer, and power electronics form an interconnected system within a wind power generation setup. Working collaboratively, these components capture wind energy, initially converting it into mechanical energy and then transforming it into electrical energy through the generator. The resulting electrical energy is then efficiently transmitted to the utility grid through the transformer and network [4, 10].

Wind turbines are categorized into variable-speed wind turbines (VSWT) and fixed-speed wind turbines (FSWT) based on their rotational speed. FSWT poses significant challenges, including considerable mechanical stress, a restricted operational speed range, and its requirement for multistage gears. In contrast, VSWTs are engineered to address these issues. By aligning with the natural variability of the wind, VSWTs can optimize power harvesting at various wind speeds, effectively reducing mechanical stress and limiting power fluctuations. The exclusive capacity to extract maximum energy is a unique feature of VSWT [4, 7].

Various electrical generators are employed in wind energy conversion systems (WECSs) designed for VSWT. Among these options, a cost-effective and reliable choice is the utilization of squirrel-cage induction generators (SCIGs), suitable for applications featuring either fixed or variable speeds. Despite their straightforward design, SCIGs encounter limitations, including constrained grid fault tolerance (GFT), utility grid's reactive power consumption, and not well-suited for gearless operation within a multiport setup [11]. Conversely, doubly-fed induction generators (DFIGs) and synchronous generators (SGs) find extensive use in WECS configurations. DFIGs, equipped with partial-scale power converters, remain economically viable but require multiple-stage gearboxes and excitation currents, making them well-suited for higher-power wind turbines [7, 12]. In contrast, the increasing favorability of permanent magnet synchronous generators (PMSGs) can be attributed to their heightened efficiency, reliability, improved FRT capability, and higher power density. These features, coupled with superior performance, make PMSGs particularly attractive for small- and medium-scale wind turbines [4].

The usage of variable-speed wind turbines is continually expanding, driven by their capability to adapt the rotor speed based on changes in wind speed. The adaptive mechanism allows these turbines to operate at peak efficiency, optimizing the power coefficient over a broad spectrum of wind speeds. Among various electrical generators, DFIG distinguishes itself as a top choice due to its favorable techno-economic characteristics. Widely employed in wind energy systems, DFIGs offer variable-speed operation, allowing for a considerable range (approximately ± 30% of synchronous speed) and facilitating the maximization of wind power extraction. Notably, they provide reactive power compensation through

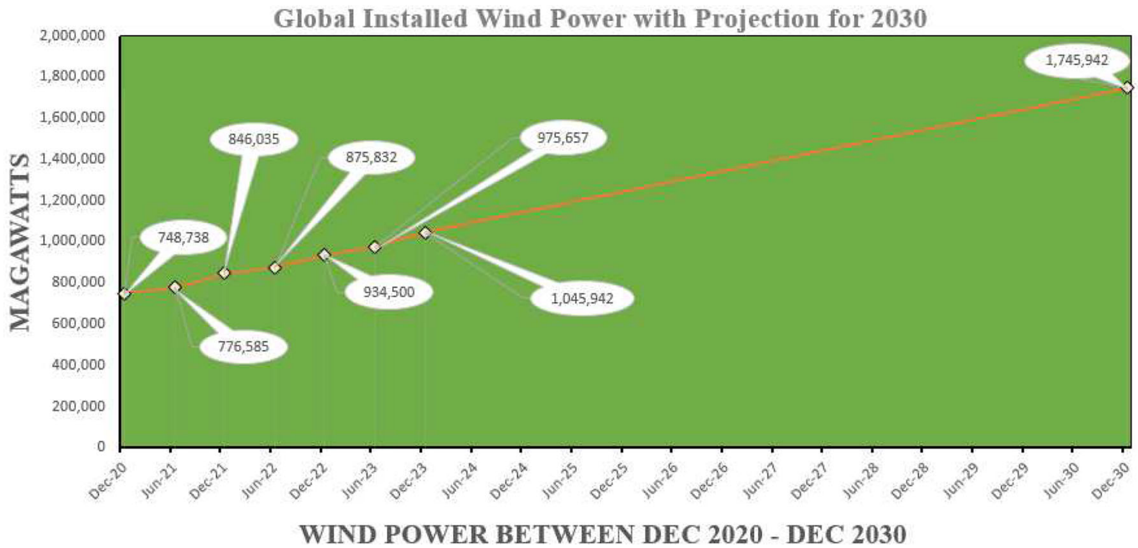

Fig. 1 Global installed wind power capacity with projected growth for 2030

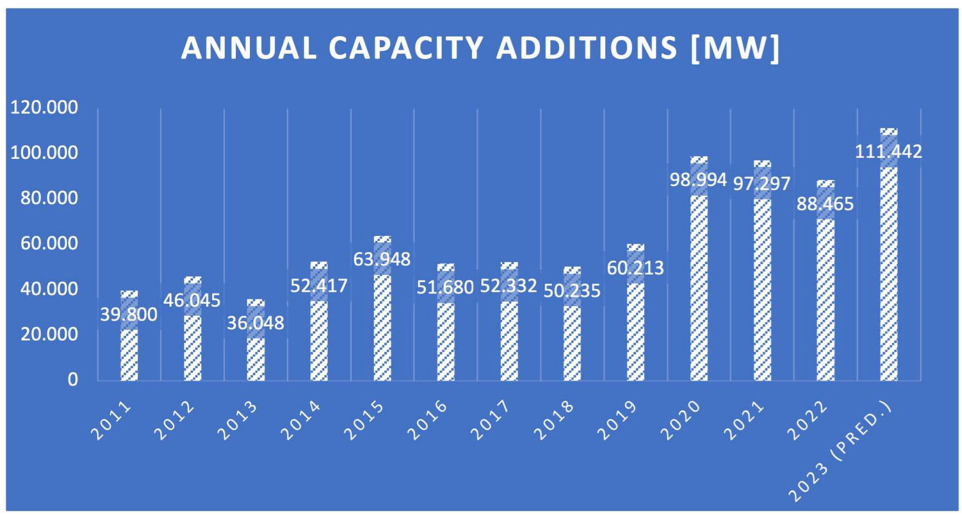

Fig. 2 Annually wind power additions from 2011 and 2023 [5]

power converters that are sized to transmit only a fraction of the nominal power (25–30%), effectively reducing losses in power electronics. Moreover, DFIGs prove to be applicable for high-power scenarios, solidifying their status as a preferred generator in wind energy systems [13, 14].

A wind turbine achieves optimal energy extraction from the wind when its rotor rotates at a speed corresponding to the velocity of the wind. The rotor speed adjusts to match the wind speed, allowing the system to operate at different frequencies [15]. To enhance power extraction from the wind, irrespective of the generator type employed, various varieties of maximum power point tracking (MPPT) algorithms are utilized. Several research studies have investigated a range of MPPT algorithms using diverse control methods [16]. This review of research explores multiple MPPT algorithms, taking into account different control strategies and conducting varied comparisons to provide a comprehensive understanding.

1.1 Modeling of WECS

1.1.1 Wind turbine

The wind turbine adeptly captures and transforms a portion of the wind's kinetic energy into mechanical power. The mathematical representation of wind kinetic energy is captured by Eq. 1, while the equations for mechanical power and torque are articulated in Eqs. 2 and 3, respectively. These formulations are in accordance with the insights presented in the references [17, 18].

$$P_k = \frac{1}{2}\rho A V^3 \quad (1)$$

$$P_m = C_p(\lambda, \beta) P_k = \frac{1}{2} C_p(\lambda, \beta)\rho A V^3 \tag{2}$$

$$T_t = \frac{P_m}{\omega_t} = \frac{1}{2\omega_t} C_p(\lambda, \beta)\rho A V^3 \tag{3}$$

In the provided context, variables ρ, A, V, $C_p(\lambda, \beta)$ and ω_t denote air density, turbine swept area, πR^2, wind velocity, wind turbine power coefficient and wind turbine speed, respectively.

The power coefficient for each wind turbine is individualized, serving as a measure of its efficiency and expressed as [18, 19]:

$$C_p(\lambda, \beta) = a_1 \left(\frac{a_2}{A} - a_3\beta - a_4\right) \exp^{-\left(\frac{a_5}{A}\right)} + a_6\lambda \tag{4}$$

where a_1, a_2, a_3, $a_4 a$, a_5 and a_6 are constants which are unique for each wind turbine blade and

$$\frac{1}{A} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3} \tag{5}$$

With

$$\lambda = \frac{\omega_t R}{V} \tag{6}$$

The coupling between the windmill's turbine shaft and the electrical generator shaft includes a gearbox, which incorporates a multiplication factor denoted as N. Equations 7 and 8 express the correlations between mechanical torque and generator torque, as well as wind turbine speed and generator speed, respectively [16, 20].

$$T_g = \frac{T_t}{N} \tag{7}$$

$$\omega_t = \frac{\omega_g}{N} \tag{8}$$

The combined inertia of a system, encompassing both the wind turbine and the generator, can be represented according to [19, 21, 22]:

$$J = \frac{J_t}{N^2} + J_g \tag{9}$$

Consequently, the mechanical shaft model is:

$$J \frac{d}{dt}\omega_g = T_g - T_{em} - f\omega_g \tag{10}$$

where the symbols J, J_g, J_t, T_t, T_{em}, and $f\omega$ correspond to total inertia, generator inertia, wind turbine inertia, mechanical torque, electromagnetic torque, and viscous friction torque, respectively.

1.1.2 Generator modeling

Considering a DFIG type, its mathematical modeling within an arbitrary d-q reference frame can be expressed through Eqs. (11) and (12) [14, 19, 23, 24].

$$\begin{cases} v_{sd} = r_s i_{sd} + \frac{d\psi_{sd}}{dt} - \omega_s \psi_{sq} \\ v_{sq} = r_s i_{sq} + \frac{d\psi_{sq}}{dt} + \omega_s \psi_{sd} \end{cases} \tag{11}$$

$$\begin{cases} v_{rd} = r_r i_{rd} + \frac{d\psi_{rd}}{dt} - (\omega_s - p\omega_m)\psi_{rq} \\ v_{rq} = r_r i_{rq} + \frac{d\psi_{rq}}{dt} + (\omega_s - p\omega_m)\psi_{rd} \end{cases} \tag{12}$$

The expression for the electromagnetic torque in the DFIG is formulated using the stator flux linkages and the rotor currents, as outlined in Eq. (13) [19, 23]:

$$T_{em} = \frac{3}{2} p \frac{L_m}{L_s} (\psi_{sq} i_{rd} - \psi_{sd} i_{rq}) \tag{13}$$

Given the presumption that the flux is exclusively oriented along the d-axis, Eq. (14) articulates the electromagnetic torque within the dq coordinate system [24].

$$T_{em} = -\frac{3}{2} p \frac{L_m}{L_s} \psi_{sd} i_{rq} \tag{14}$$

The expression for the stator currents in the dq coordinate system is conveyed through Eq. (15), as documented in the reference [24].

$$\begin{cases} i_{sd} = \frac{\psi_{sd}}{L_s} - \frac{L_m}{L_s} i_{rd} \\ i_{sq} = -\frac{L_m}{L_s} i_{rq} \end{cases} \tag{15}$$

1.2 Overview of MPPT control methods in WECSs

The wind turbine plays a key role in converting kinetic energy into mechanical energy and subsequently transforming it into electrical energy. This process requires various converter types to seamlessly integrate the generated electrical energy with the grid. Essential for comprehensive control, these converters operate on both the generator side and grid side. This dual control ensures that the WECS can precisely meet power grid requirements, adapting to varying wind speeds. To obtain the maximum possible power from WECS, a controller is indispensable, incorporating an algorithm for MPPT [21, 25].

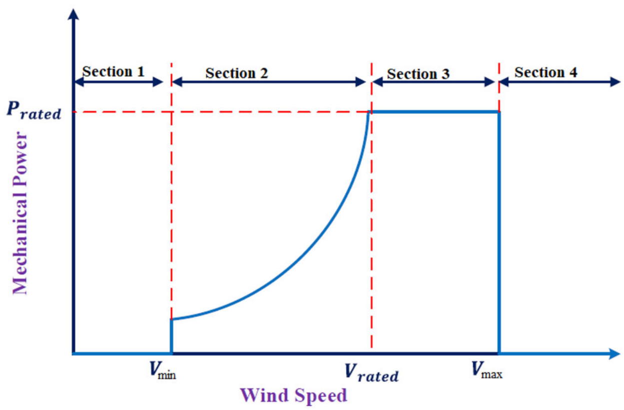

Fig. 3 Various operating sections in variable-speed wind systems [29]

The reliability of wind power is contingent upon the unpredictable shifts in weather and the capricious nature of wind velocities. Therefore, conducting a thorough analysis of wind characteristics is vital to establish operational parameters for effective integration into the grid, particularly in response to variable wind speeds [26]. This procedure allows for the exact adjustment of wind turbines, enabling them to capture available wind energy within precisely defined wind speed ranges. The range can be defined between minimum speed (V_{min}) and maximum speed (V_{max}), as illustrated in Fig. 3. The operational timeline of the flexible WECS is subsequently categorized into four distinct sections, depending on wind speed values. This classification is visually presented in Fig. 3 [27, 28].

Each section of Fig. 3 is described below:

- Section 1: During the parking mode ($V_w < V_{\text{min}}$), characterized by low wind speeds, the machine is unable to generate electric power and remains in a non-power-producing state.
- Section 2: This section is denoted as the MPPT control mode ($V_{\text{min}} < V_w < V_{\text{rated}}$), employing MPPT algorithms to effectively capture the utmost available power from wind energy. The MPPT algorithm dynamically adjusts to the optimal power point corresponding to various wind speeds, all the while keeping the blade pitch angle consistently at zero.
- Section 3: During the pitch control mode ($V_{\text{rated}} < V_w < V_{\text{max}}$), When wind speed surpasses the designated threshold, pitch control is engaged to manage the generated electric power, maintaining it within the predetermined nominal value.
- Section 4: In the parking mode, characterized by an inability to maintain reliable performance, pitch angle is optimized to its maximum, and a braking system is utilized to securely stop the wind turbine's operation.

The relationship between λ_{opt} and $C_{p_{\max}}$ is depicted in Fig. 4, providing insights into the concept of maximum power point (MPP) for WECS [30]. This paper zeroes in on this particular domain where the MPPT control algorithm becomes applicable.

To effectively track and harness the maximum power possible from wind energy, the incorporation of an MPPT algorithm method is indispensable. These MPPT control algorithms can be classified into different groups depending on the information required to design the control algorithm [31, 32].

- MPPT algorithms that fall into this category require a fundamental understanding of wind turbine characteristics or rely on wind speed measurements. MPPT control techniques like tip speed ratio method, power signal feedback method, and optimal torque control method are included in this group [33].
- In the second category, information about wind turbine characteristics is considered unnecessary, and the system operates independently of wind speed measurements. MPPT control techniques, like Perturb and Observe method, Optimal Relation-Based method, and Incremental Conductance method, are categorized within this class [34].
- In the third category, a hybrid control technique is applied, combining two or more MPPT control algorithms. This hybrid approach utilizes the strengths of each control algorithm while addressing their respective limitations [35]. Different hybrid techniques are explored in this review paper, including hybrid conventional algorithms, hybrid intelligent algorithms, hybrid conventional-intelligent algorithms, and hybrid fractional-order-intelligent algorithms.
- In the final category are intelligent MPPT algorithms, which operate independently of wind turbine characteristics. Depending on the specific algorithm, these may or may not require wind speed measurements. This category encompasses control methods, including algorithms like neural networks (NN), fuzzy logic controllers (FLCs), and other intelligent algorithms [36].

Moreover, a diverse array of hybrid control algorithms has been developed, seamlessly integrating MPPT algorithms with optimization techniques to effectively extract the maximum power possible from WECS. Furthermore, a noteworthy approach involves the application of fractional-order intelligent algorithms, combining fractional-order control techniques with advanced intelligent algorithms. This innovative combination serves to elevate the MPPT capabilities of a wind power system. By integrating fractional-order control techniques with intelligent algorithms, such as artificial neural networks or evolutionary algorithms, this hybrid con-

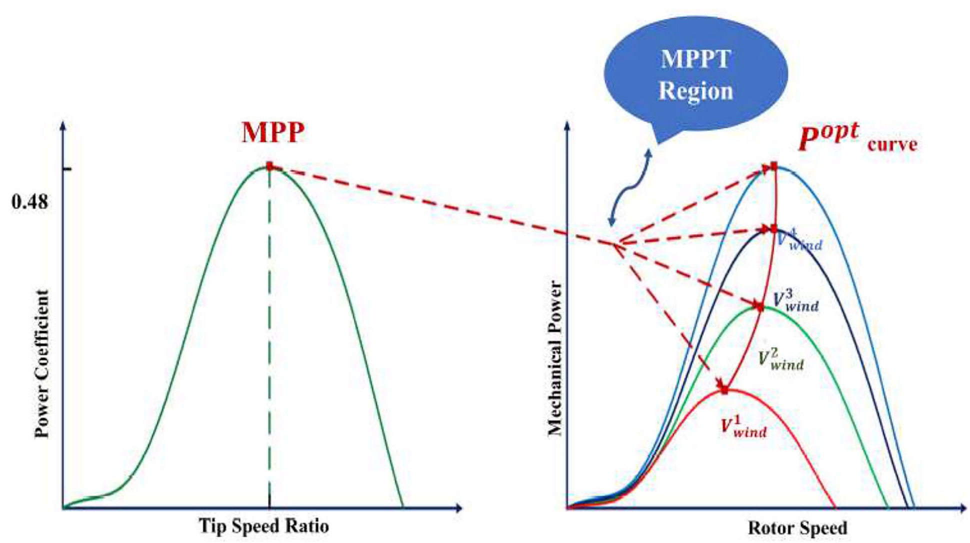

Fig. 4 MPP for different wind speeds at optimal value of λ_{opt} and $C_{p_{max}}$ [30]

trol system excels in adaptively optimizing the extraction of power from the wind resources. This dual-pronged strategy not only enhances the overall performance of the system but also ensures optimal power output in diverse environmental conditions, establishing it as a resilient and efficient solution for maximizing the conversion of wind energy [33].

Several review articles provide in-depth insights into MPPT control techniques specifically designed for WECS. In this review paper, we examine diverse control algorithms, spanning both historical and contemporary methods, used to track and optimize power output in WECS. Additionally, we explore intelligent and hybrid variants of these control algorithms as documented in existing literature. These control techniques are categorized based on direct power control and indirect power control, as well as hybrid and intelligent MPPT control algorithms. We have conducted comparisons, considering features such as adaptability, computational complexity, efficiency, oscillation, overall expenses, robustness, speed of convergence, storage, time response, as well as factors like the requirement of wind speed measurement and wind turbine's characteristics.

The following sections in this review paper are structured as: Section 2 provides an in-depth exploration of the classification and detailed description of MPPT control algorithms, along with a compilation of references related to these control methods. The discussion of our findings is presented in Sect. 3, and Sect. 4 delves into current trends and future prospects. Finally, Sect. 5 concludes the paper with a brief summary of our findings.

2 MPPT control algorithms for WECSs

Wind energy availability experiences continuous fluctuations due to varying wind speeds throughout the day. The effectiveness of WECS relies heavily on the accuracy of MPPT control techniques, which optimally traces maximum power points, irrespective of the generator type used in the system. The overarching objective of MPPT is to enhance WECS efficiency by optimizing the extraction of maximum possible power from wind energy resources [37].

MPPT methods for WECS fall into two main categories: conventional and intelligent algorithms. Conventional approaches comprise indirect power control (IPC) techniques, involving the tracking of mechanical power, and direct power control (DPC) techniques, concentrating on maximizing electrical power output [30]. Intelligent algorithms utilize artificial intelligence (AI) or computational intelligence techniques [38]. MPPT methods are broadly classified as DPC, IPC, hybrid and intelligent control algorithms, as illustrated in Fig. 5. Algorithms employed by IPC include: tip speed ratio (TSR) method, power signal feedback (PSF) method, and optimal torque control (OTC) method, whereas perturb and observe (P&O) method, incremental conductance (INC) method, and optimal relation-based (ORB) method are included under DPC. The hybrid control scheme cleverly combines multiple MPPT algorithms to overcome inherent limitations in individual categories. Intelligent algorithms, crucial for addressing complex problems, have become indispensable in WECS applications by eliminating the need for precise mathematical parameters in the system [15].

Some control techniques necessitate accurate turbine parameters and wind speed measurements, while others dispense with the need for direct wind speed measurements, but require the use of estimators. Recent advancements have led to control techniques that no longer require the measurement of any physical parameter. Instead, they rely on conventional algorithms enhanced in performance through the integration of intelligent control algorithms. This paradigm shift marks

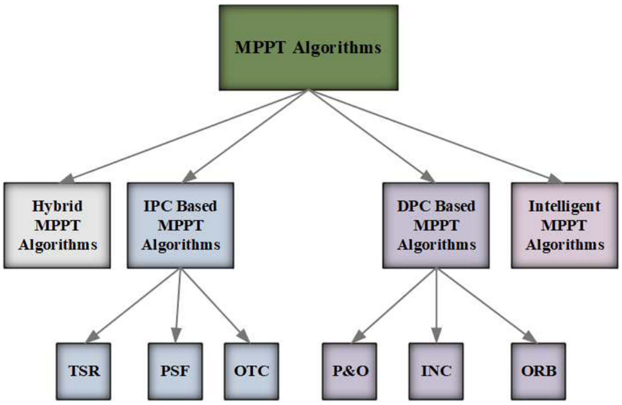

Fig. 5 Different MPPT control algorithm classifications

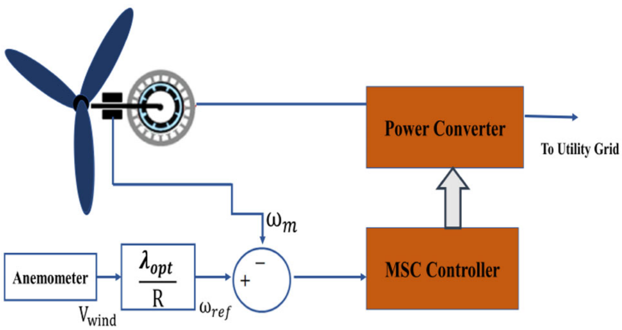

Fig. 6 TSR MPPT algorithm [38]

a progressive leap toward more efficient and adaptive wind energy systems [37, 39].

2.1 Conventional indirect power control method

2.1.1 Tip speed ratio method

In the pursuit of optimizing power extraction, the tip speed ratio (TSR) method, which represents the ratio of turbine speed to wind speed, is specifically crafted to uphold this value at its optimal level. This entails the quest for optimal rotor speed (ω^*) by measuring or estimating both wind speed and turbine speed [38, 40]. A profound comprehension of system parameters is indispensable in this process, as illustrated in Fig. 6. The implementation of the TSR algorithm significantly influences the effectiveness of regulating the optimal rotor speed under various environmental conditions. This effectiveness can be attributed to its characteristics of simplicity, high efficiency, and swift responsiveness, as discussed in [36].

Wind speed can be determined either through direct measurement using a wind speed sensor or an estimation method. The former involves a mechanical sensor, but this method is associated with drawbacks such as high initial costs, increased maintenance expenses, and diminished performance [10, 30]. The latter approach employs a wind speed estimation algorithm, and depending on the application, the estimation may be based on mathematical modeling or intelligent controllers, offering improved efficiency, fast speed, and simplicity [14, 41].

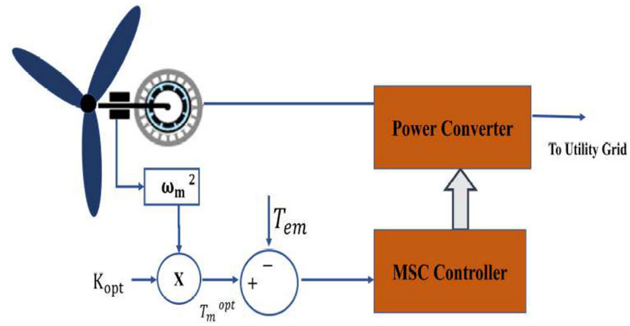

Fig. 7 OTC MPPT algorithm [30]

2.1.2 Optimal torque control method

The optimized torque graph is intricately linked to the control of generator torque within the optimal torque control (OTC) method, visually demonstrated across a range of wind speeds in Fig. 7 [30]. The implementation of this methodology not only yields significant benefits, including heightened efficiency, increased flexibility, and simplified processes, but also ensures a consistent regulation of torque [42]. However, despite these advantages, its susceptibility to climatic fluctuations emphasizes the importance of thoroughly understanding the specific attributes of the wind turbine. This encompasses assessing its adaptability to changing environmental conditions, ensuring a resilient and dependable performance in various circumstances. Therefore, the effective application of the OTC control technique requires a detailed understanding of wind turbine characteristics and adept management of external factors that could influence its performance [32, 38, 43].

2.1.3 Power signal feedback method

The power signal feedback (PSF) method necessitates both the data for the maximum power curve and a power reference to function optimally. Typically, determining the maximum power curve for each wind turbine involves offline experiments or software simulations [44]. To establish the reference power, one can either use recorded maximum power data or apply the mathematical calculation of mechanical power, with wind speed or rotor speed as input parameters [37]. Despite their robustness and cost-effectiveness, both the OTC and PSF control methods encounter challenges in effectively tracing the MPP when the wind speed is low, particularly in large-inertia wind turbines. While the PSF and OTC methods

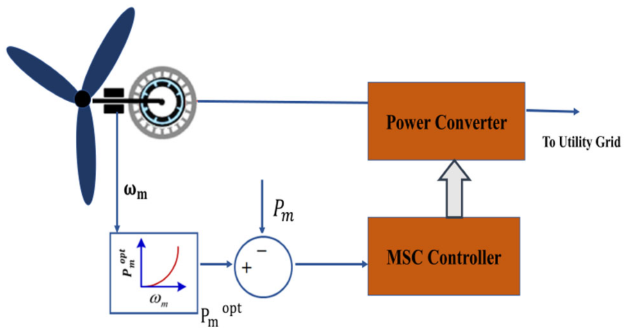

Fig. 8 PSF MPPT algorithm [30]

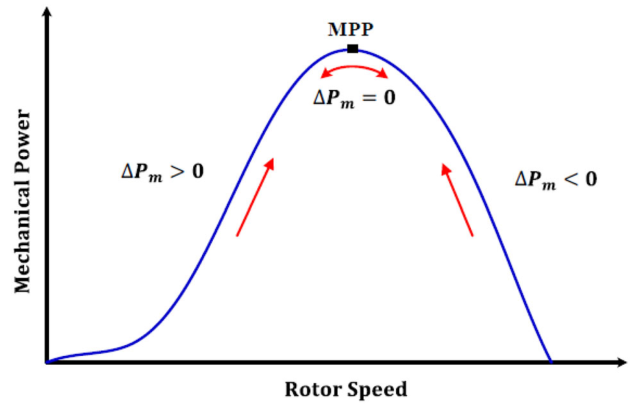

Fig. 9 Operation concept of P&O [38]

eliminate the need for mechanical sensors, they still require precise knowledge of the wind turbine's parameters. The control strategy for the PSF is depicted in Fig. 8 [30, 43] (Table 1).

2.2 Conventional direct power control method

2.2.1 Perturb and observe method

The perturb and observe (P&O) utilizes mathematical optimization to search the MPP of a system. The principle of P&O control techniques involves perturbing the control variable in fixed step-sizes, which is the rotational speed of the generator in case of WECS, and observing the expected electrical output power [47]. The current operating point determines the direction of the perturbation, regardless of whether it is situated on the left or right side of the graph of mechanical power versus generator speed. If the current working point is to the left of optimal value, the search direction is to the right, moving closer to the MPP until the slope of the power-speed curve is zero, vice versa if the current working point is on the opposite side as illustrated in Fig. 9 [30, 37, 39]. As this method does not require wind turbine characteristics and wind speed measurements, it offers advantages over other control techniques [48].

The conventional perturb and observe (CPO) control technique employs a fixed step size to perturb the control variable and observe the electrical power result. Consequently, CPO struggles to attain the MPP when wind speed fluctuates, as depicted in Fig. 10 [49]. When the chosen step size is large, the algorithm quickly tracks the MPP, but oscillations occur when it reaches the MPP. Conversely, using a small step size improves the system's effectiveness, but reaching the MPP takes a considerable amount of time. This indicates that the control method could face challenges when attempting to track the MPP in the presence of rapidly fluctuating wind conditions [33].

Moreover, selecting optimal step size presents a primary challenge in the P&O method. An incorrect step size may lead to inaccurate tracking directions, potentially causing the algorithm to diverge from the peak power. Therefore, if the algorithm's step size is not chosen correctly, consequences such as power loss, oscillations, reduced efficiency, and delayed control response may ensue [15, 38]. Figures 11

Table 1 Comparison of the characteristics of conventional indirect power control MPPT algorithms [30, 38, 42, 44–46]

MPPT algorithm features	TSR	OTC	PSF
Adaptability	Average	Average	Average
Computational complexity	Minimal	Minimal	Minimal
Efficiency	Superior	Intermediate	Superior
Oscillation	Not Present	Not Present	Not Present
Overall expense	Expensive	Average	Average
Robustness	Not robust	Relatively robust	Relatively robust
Speed of convergence	Fast	Fast	Fast
Storage	Not available	Available	Not available
Time response	Intermediate	Intermediate	Intermediate
Wind speed measurement	Present	Absent	Absent
Wind turbine characteristic	Not mandatory	mandatory	mMandatory

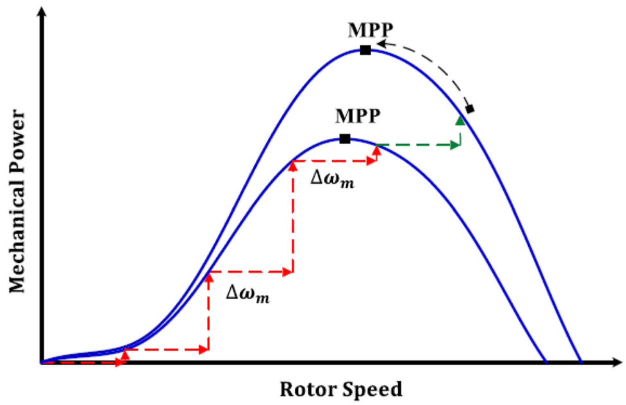

Fig. 10 When P&O is losing track under wind speed fluctuating [38]

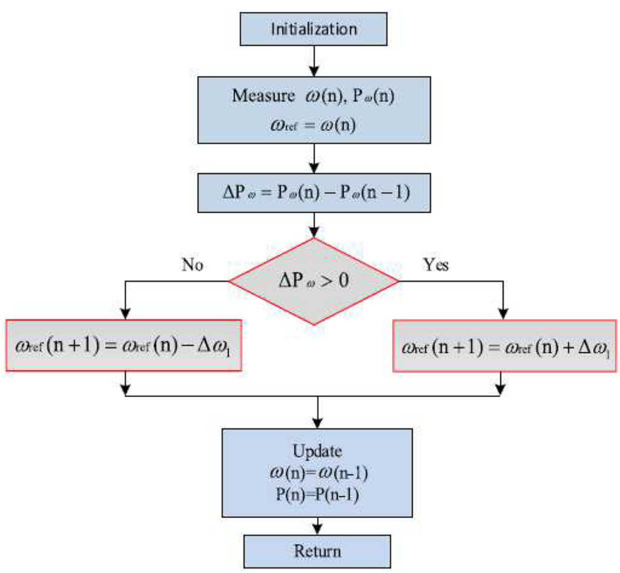

Fig. 11 P&O flowchart [38]

and 12 illustrate the flowchart and block diagram of the P&O algorithm, respectively.

2.2.2 Incremental conductance method

The incremental conductance (INC) control technique stands out for its ability to eliminate the necessity for sensors and foreknowledge of wind turbine (WT) parameters, resulting in a notable improvement in both reliability and efficiency. By solely observing the power output generated by the converter and calculating the slopes of the power variations, this method determines both the MPP and perturbation directions [50]. Adaptive INC control method goes a step further in

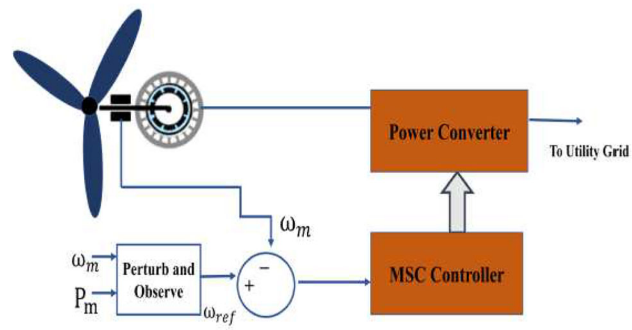

Fig. 12 P&O algorithm [38]

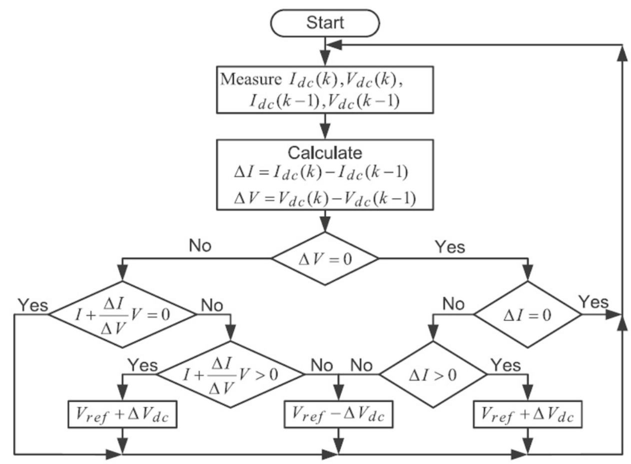

Fig. 13 Modified INC algorithm flowchart [52]

refining the dynamic performance and convergence speed of WECS. It is important to underscore, however, that the scope of viable step sizes is restricted and relies on the parameters of a generator [42, 43, 51].

The fundamental concept behind the basic INC method lies in the slope of the power-voltage characteristic equation, where the slope becomes zero precisely at the MPP. The slope equation is [52]:

$$\frac{i_{dc}}{v_{dc}} + \frac{di_{dc}}{dv_{dc}} = 0 \tag{16}$$

This method track MPP based on the rectifier output as Eq. 16 independent of weather conditions like speed or direction of the wind. The modified INC control method uses adaptive step size for v_{dc} as depicted in Fig. 13 to enhance the performance of tracking ability.

In various scholarly publications, researchers apply the dynamic INC control technique to forecast the ideal alteration step size, enhance the disturbance direction, and precisely

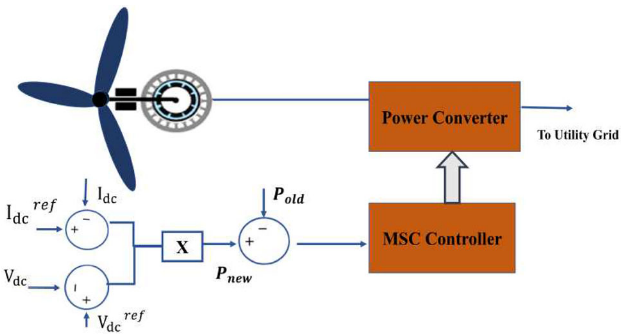

Fig. 14 MPPT algorithm of INC [30]

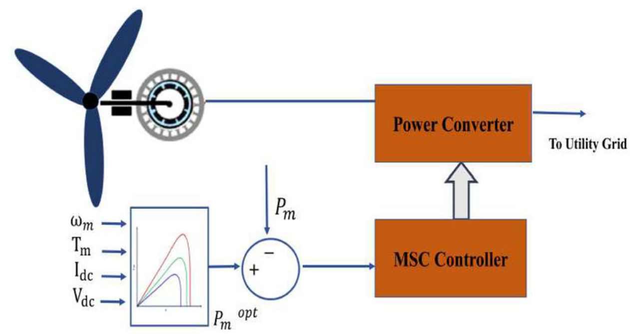

Fig. 15 MPPT algorithm Of ORB [30]

follow the MPP [30, 38]. This adaptive feature enhances the adaptability and efficiency of the INC algorithm in diverse operational scenarios. Furthermore, the adaptability of perturbation step sizes becomes particularly critical in optimizing the performance of WECS under varying conditions. The control technique of the INC is visually depicted in Fig. 14, providing a comprehensive overview of its operational structure and highlighting its integration within the broader context of wind energy systems.

2.2.3 Optimal relation-based method

In the domain of optimal relation-based (ORB) control technique, the pursuit of MPPT is accomplished through the optimization of relationships among various system variables. These encompass power and rotor speed, electromagnetic torque and output power, and DC-based power systems [53, 54]. The allure of ORB control lies in its straightforward implementation, impressive dynamic response, and independence from wind speed sensors. Notably, it tends to generate a smoother output power profile in comparison with alternative strategies. However, it is imperative to acknowledge a key limitation of ORB control-its reliance on system-specific pre-knowledge. This prerequisite can exhibit variability across different systems and evolve as the system ages. This demand for prior knowledge introduces a potential challenge, particularly in scenarios where accurate information might be difficult to obtain or subject to change. Moreover, it is worth noting that the application of ORB control may require a considerable amount of storage, a factor that should be considered in the design and implementation stages [30, 54]. Figure 15 shows the algorithm of ORB.

Table 2 presents a comparison of the characteristics of various DPC MPPT algorithms.

2.3 Modified conventional MPPT algorithms

The MPPT algorithm methods mentioned above, which are of a traditional nature, have successfully monitored the MPP of WECS. However, each method has its own drawbacks. As a result, developing a an MPPT algorithm for a precise MPP monitoring remains a significant challenge. In an attempt to tackle these challenges, certain researchers have made modifications to the conventional methods [55]. Table 3 discusses the conventional MPPT algorithms and their modified counterparts.

2.4 Intelligent MPPT algorithms

In WECS, various intelligent control methods, including fuzzy logic control, neural networks, and other sophisticated methods, have been employed for MPPT applications [14, 61, 62]. Additionally, different optimization strategies have been utilized in the MPPT of WECS [63–67]. The integration of these intelligent algorithms and optimization methods aims to address the inherent limitations in conventional MPPT algorithms, ultimately enhancing the overall system performance. Intelligent algorithms have emerged as a pivotal tool, providing a significant advantage by eliminating the need for precise mathematical parameters [56]. In this paper, we categorize Intelligent MPPT algorithms into four groups: fuzzy logic controller (FLC), neural networks (NNs), intelligent sensorless techniques, and multi-variable perturb and observe (MVPO) MPPT algorithms, as illustrated in Fig. 16 [68, 69]. Subsequently, we provide a concise overview of each category.

2.4.1 Fuzzy logic controller method

Fuzzy logic controllers (FLCs) are applied in MPPT algorithms for WECS to attain swift responses and alleviate oscillations around the MPP. This proves advantageous in scenarios where precise mathematical modeling of WECS is challenging. However, the effectiveness of FLCs relies on the designer's expertise in determining factors such as the appropriate error surface, membership function levels, and the selection of a rule-based layer, which may demand a significant amount of memory space [70–72]. The funda-

Table 2 Comparison of the characteristics of conventional direct power control MPPT algorithms [30, 38, 44–46, 52]

MPPT algorithm features	CPO	INC	ORB
Adaptability	Average	Average	Average
Computational complexity	Easy	Easy	Easy
Efficiency	Minimal	Minimal	Intermediate
Oscillation	Present	Present	Not present
Overall expense	Average	Average	Expensive
Robustness	Relatively robust	Relatively robust	Not robust
Speed of convergence	Sluggish	Sluggish	Intermediate
Storage	Not mandatory	Not mandatory	Not mandatory
Time response	Relatively fast	Intermediate	Intermediate
Wind speed measurement	Absent	Absent	Absent
Wind turbine characteristics	Not mandatory	Not mandatory	Not mandatory

Table 3 Comparison of various conventional MPPT algorithm techniques and their modified versions [30, 36, 38, 42–44, 51]

MPPT algorithm	Merits	Significant limitations	Modification
TSR	TSR boasts the benefits of simplicity and swift convergence speed. Furthermore, it operates without necessitating memory for the procedure	Several anemometers, with precision levels between 5 and 10%, are strategically located across wind turbine's covered expanse to evaluate the effective wind velocity. This leads to a decline in the overall dependability and performance, primarily attributable to the substantial starting and ongoing costs	To address the limitations of wind velocity sensors, different researchers propose Wind Speed Estimation (WSE) algorithms. WSE is employed to reduce errors associated with mechanical speed sensors, thereby improving both the precision and speed of tracking the maximum power point (MPP) [14]
OTC	OTC provides benefits like uncomplexity, resilience, and efficient tracking, resulting in heightened overall performance. The employed MPPT algorithm's practicality, independent of real-time wind speed sensor, reduces initial and maintenance costs. This cost-effective aspect makes OTC an attractive and sustainable solution for optimizing energy capture, offering economic and operational advantages	This algorithm utilizes weather conditions and prior knowledge of wind turbine characteristics. Integrating turbine speed and electromagnetic torque measurements can raise costs and is contingent on generator parameters	The effectiveness of MPPT-OTC methods in wind turbine systems has been elevated through the incorporation of intelligent algorithm introduced by [56], showcasing superior performance compared to traditional OTC. Additionally, [57] proposed a fuzzy logic-based MPPT algorithm to enhance OTC, ensuring improved performance, particularly under varying wind velocities in which system stability is maintained
PSF	The PSF algorithm offers reliable performance in varying wind speeds, swift convergence for efficient tracking, absence of oscillations at the maximum power point (MPP), robustness, and a cost-effective profile. These features make PSF preferable and economically efficient solution for optimizing power generation in wind turbine systems	Compared to TSR and OTC, the PSF method shows increased complexity and decreased effectiveness. The incorporation of mechanical wind speed measurement introduces the potential for errors, and this approach heightens the risk of generator stalling during sudden changes in wind speed, depending on prior knowledge of wind turbine characteristics	To prevent generator stalling, an adjustment is implemented by offsetting the measured power with a constant value. However, this modification introduces a challenge, as it leads to undesired overshooting in the control variable, sophisticating the accurate tracking of the MPP [36]

Table 3 continued

MPPT algorithm	Merits	Significant limitations	Modification
P&O	This algorithm mitigates the need for a wind speed sensor, bypasses the necessity for prior comprehension of system parameters and characteristics, and requires less memory, resulting in diminished overall system costs. Additionally, it demonstrates moderate performance and robustness, especially in situations marked by irregular wind speeds	A significant drawback of this algorithm is the challenge in selecting a suitable step size for perturbation, directly impacting the performance of the wind turbine. Larger step sizes induce oscillations near the maximum power point (MPP), whereas smaller step sizes result in extended convergence time and a slowed response. Another concern is the potential for losing track of the MPP during variations in wind speed	The refinement in CPO involves a strategic adjustment in the tracking approach, resulting in Modified Perturb and Observe algorithms (MPO). These enhancements include variable, adaptive, and hybrid step size methodologies to address the limitations in CPO [58, 59]. This adaptive evolution aims to improve overall performance and effectiveness in optimizing energy capture in dynamic environmental conditions
INC	This algorithm bears resemblances to the perturb and observe (P&O) method; however, it sets itself apart by demonstrating preeminent speed convergence and enhanced tracking Competence. These advancements underscore its capacity to more swiftly and accurately adapt to dynamic conditions, showcasing a notable improvement over the traditional P&O approach	This algorithm exhibits a sluggish pace in achieving speed convergence, along with suboptimal efficiency and noticeable oscillations observed at MPP	Incorporating the concept of adjusting perturbation step sizes, INC algorithms seamlessly enhance the performance of the system while simultaneously accelerating the speed of convergence [30]
ORB	This algorithm stands out for its quick response and easy operation, eliminating the need for wind speed sensors. Additionally, comparing to P&O and INC methods, it showcases superior convergence speed. Importantly, there is no occurrence of oscillation around maximum power point (MPP)	This algorithm imposes a substantial memory requirement for storing the pre-established optimal relation curve, thereby mandating a prerequisite understanding of the system	In the evolution outlined in References [36, 60], the ORB method underwent changes by seamlessly integrating the P&O method as an initiation for real-time exploration of MPP at local wind velocities. Through this integration, a limitation of the ORB method was effectively addressed by extracting vital parameters essential for its efficient operation

mental structure of FLC is depicted in Fig. 17. Fuzzification transforms input variables into fuzzy sets, and the rule base comprises IF-THEN rules defining relationships between input fuzzy sets and corresponding output fuzzy sets. The control rules evaluate the rules based on current fuzzy input values. The final step, defuzzification, converts the fuzzy output into a precise numerical value for system control [52, 73]. Numerous articles have proposed diverse FLC strategies within the context of MPPT algorithms, as discussed in the literature [31, 69, 74–76]. Figure 17 illustrates the FLC scheme.

In the study [77], three MPPT control strategies such as PI, P&O, and FLC were assessed for their efficacy in optimizing wind energy systems in the presence of fluctuating wind speeds. The analysis revealed that PI struggled to track maximum power due to system nonlinearity, while P&O exhibited good performance but oscillated around the optimal value with varying wind speeds. In contrast, FLC emerged as a

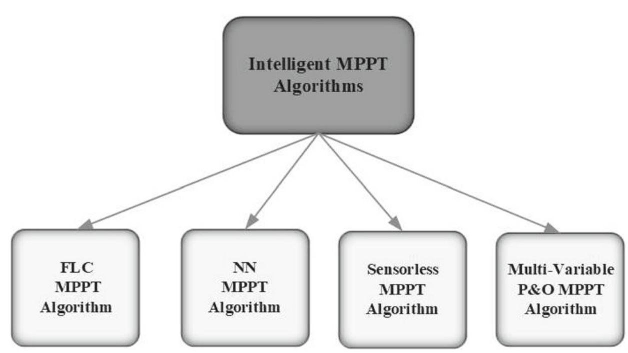

Fig. 16 Classification of intelligent MPPT algorithms

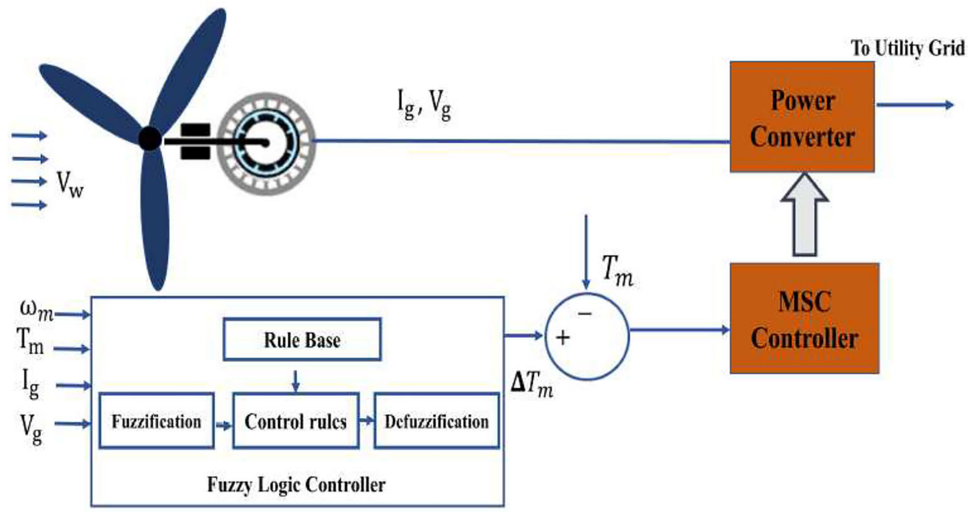

Fig. 17 Basic structure of fuzzy logic controller algorithm [71]

superior control technique, demonstrating fast and efficient power optimization. The results underscored FLC's superiority over PI and P&O in terms of stability, rapid tracking ability, and time response, particularly in the face of unpredictable wind speed fluctuations. Similarly, in the assessment detailed in [78], a comprehensive comparison of overall efficiency, considering speed response and tracking ability for maximum power, was undertaken among FLC, TSR, and PSF in the domain of wind energy. The findings revealed that FLC attained an efficiency of 92%, outperforming TSR at 85.44% and PSF at 87.12%. This result indicates that FLC demonstrates superior performance with a higher overall efficiency compared to TSR and PSF.

In the paper [79], a comparison was conducted between FLC and Hill Climb Search (HCS) based on parameters such as oscillation and time responses. The results indicated that FLC exhibited less oscillation and faster responses compared to HCS. Additionally, in [80], a variable step−size-based fuzzy logic controller was introduced for the MPPT of a wind energy system, and its performance demonstrated effective and prompt responses to changes in wind speed.

2.4.2 Neural network method

MPPT control method based on neural network constitutes a specific approach within the MPPT domain, utilizing artificial neural networks to optimize the power output of wind turbines. Neural networks are structured around a fundamental and intricate design, featuring three essential layers: the input layer, one or more intermediate layers, and the output layer, as illustrated in Fig. 18 [81, 82]. The input layer acquires the initial data. The intermediate (middle) layer, which is between the input and output layers, applies transformations to the input data. And final outcomes of the network are generated by the output layer. The output layer of the neural network produces the final results of the network [83–86]. The system is trained utilizing specific input–output patterns, resulting in a decreased response time. This capability allows the system to swiftly reach a stable state, even in the presence of changing wind velocities. Such an approach contributes to enhancing the equilibrium between response time and output power [1, 21, 36].

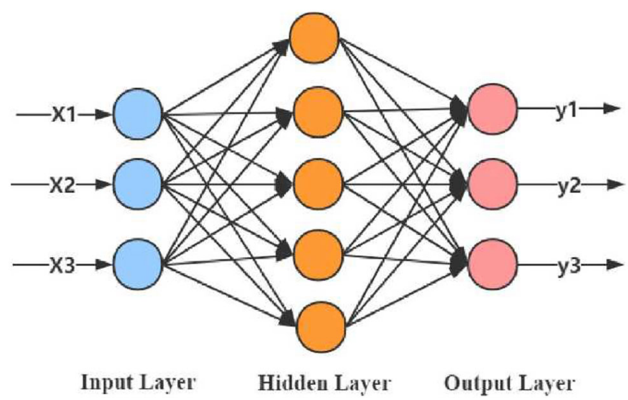

Fig. 18 Basic architecture of neural network [1]

The investigations presented in [87, 88] explore varied approaches to MPPT in WECS. In [87], a comparison is made between an artificial neural network (ANN) and a proportional-integral (PI) controller. This evaluation centers on their steady and evolving performance, as well as time response. The outcomes indicate that the ANN outperforms the PI controller, demonstrating superior performance and a more rapid time response. In [88], an evaluation of the proposed radial-based function neural network (RBF-NN) for MPPT is conducted, comparing it against back-propagation-based neural network (BP-NN), FLC, and P&O. The assessment takes into account parameters such as overshoot, ripples, oscillation, and overall performance. The results indicate that the RBF-NN controller displays reduced

Table 4 Comparison of the characteristics of intelligent MPPT algorithms [30, 38, 42, 45, 46, 52, 54]

MPPT algorithm features	FLC	NN	ISMPPT	MVPO	Others
Adaptability	Excellent	Excellent	Excellent	Average	Average
Computational complexity	Greater	Greater	Greater	Greater	Intermediate
Efficiency	Superior	Superior	Average	Average	Depends on the algorithm
Oscillation	Absent	Absent	Depends	Absent	Depends on the algorithm
Overall expense	Expensive	Expensive	Cheap	Cheap	Depends on the algorithm
Robustness	Robust	Robust	Relatively robust	Relatively robust	Relatively robust
Speed of convergence	Intermediate	Intermediate	Intermediate	Sluggish	Intermediate
Storage	Present	Present	Present	Present	Depends on the algorithm
Time response	Fast	Fast	Depends	Depends	Depends on the algorithm
Wind speed measurement	Conditional	Conditional	Not mandatory	Not mandatory	Depends on the algorithm
Wind turbine characteristics	Mandatory	Mandatory	Not mandatory	Not mandatory	Depends on the algorithm

oscillation, a minimal ripple factor of (2%), and minimal overshoot. This emphasizes its swift, effective, and dependable performance in tracking the MPP compared to other controllers.

2.4.3 Intelligent sensorless method

Intelligent sensorless maximum power point tracking (ISMPPT) methods are designed to optimize the performance of wind turbines without the need for dedicated wind speed measurements and prior knowledge of the turbine specifications [85, 89]. These algorithms aim to identify the most efficient operating state of the wind turbine by utilizing available data, such as generator power output or electrical signals. This eliminates the need for direct measurements of wind speed or direction [90–92].

Intelligent sensorless algorithms commonly leverage mathematical models, estimators, or adaptive control strategies to deduce or estimate relevant parameters without relying on direct sensor measurements [93]. Prevalent approaches for sensorless MPPT in wind energy include model-based estimation (MBE), adaptive control, and observer-based estimation (OBE) techniques. The primary objective of sensorless MPPT algorithms is to reduce costs associated with sensor installation, maintenance, and calibration, thereby enhancing the economic viability of wind energy systems. However, the effectiveness of these algorithms depends on the precision of the employed models and estimators and may face challenges in highly dynamic and variable wind conditions [45].

2.4.4 Multi-variable perturb and observe method

The primary goal of the multi-variable perturb and observe (MVPO) method is to maximize power generation in a wind power plant while simultaneously minimizing the number of wind speed measurements and the required control units [94]. MVPO achieves an elevated power output with a reduced number of components in the wind farm infrastructure. By employing the MVPO algorithm, it becomes feasible to optimize the current output of each generator individually. This is accomplished through systematic perturbations of the current for each generator until an overall increase in power output is observed across the entire wind farm. This iterative process is methodically applied to cover each generator within the wind farm, demonstrating the algorithm's efficiency and adaptability [52].

Table 4 displays the comparison of characteristics of various Intelligent MPPT algorithms.

2.5 Hybrid MPPT algorithms

Hybrid MPPT in wind energy entails integrating diverse MPPT techniques to optimize wind turbine performance. This approach melds traditional algorithms with intelligent or optimization-based methods. Through the amalgamation of these varied strategies, hybrid MPPT aims to harness their individual strengths, mitigate limitations, and enhance the overall efficiency and adaptability of wind energy systems. As a result, hybrid MPPT methods are categorized into hybrid conventional–conventional MPPT algorithms, hybrid conventional–intelligent MPPT algorithms, hybrid intelligent–intelligent MPPT algorithms, optimization-based hybrid MPPT algorithms, and hybrid fractional-order-intelligent MPPT algorithms, as depicted in Fig. 19. In this section, we will examine a range of hybrid MPPT control techniques that have been developed in recent times, aiming to enhance the efficiency of conventional techniques.

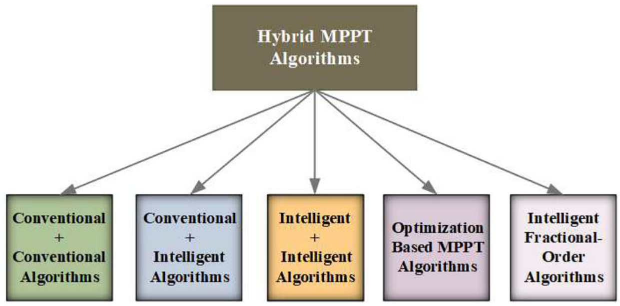

Fig. 19 Classification of hybrid MPPT algorithm

2.5.1 Hybrid conventional–conventional algorithms

Hybrid conventional–conventional MPPT algorithm integrates multiple conventional MPPT control techniques to enhance the efficiency of tracking MPP. This method brings about increased energy generation, efficiency, and resilience compared to using individual algorithms separately, resulting in an overall enhancement of system performance [60].

2.5.2 Hybrid conventional-intelligent algorithms

The integration of conventional and intelligent MPPT algorithm is designed to enhance system performance. By leveraging the strengths of both approaches, these hybrid algorithms can improve the precision and speed of tracking the maximum power point, ultimately boosting energy efficiency and power output [35, 76]. Intelligent algorithms exhibit the capacity to tackle intricate issues, and when integrated with traditional algorithms, they bolster the technique's robustness, efficiency, and reliability. According to existing research, the drawbacks of traditional algorithms have been mitigated, resulting in enhanced tracking speed and increased accuracy [76, 95].

2.5.3 Hybrid intelligent-intelligent algorithms

Hybrid intelligent–intelligent MPPT in wind energy involves incorporating intelligent control strategies to enhance the performance of wind turbines. This method integrates intelligent MPPT algorithms, such as neural networks, fuzzy logics, or other artificial intelligence methods. The integration of intelligent components empowers the system with the capability to adapt to unstable weather conditions, leading to enhanced system performance. This adaptation ensures the extraction of maximum power from the system under diverse weather circumstances. The hybrid nature of these algorithms offers a flexible and robust solution for optimizing power output in variable wind conditions [31, 64].

2.5.4 Optimization-based hybrid algorithms

Hybrid MPPT algorithms frequently integrate multiple optimization techniques to improve the efficiency and robustness of the MPPT process. Among these optimization techniques such as particle swarm optimization (PSO) algorithm, genetic algorithms (GA), and ant colony optimization (ACO) algorithm are among the commonly utilized optimization techniques in hybrid MPPT method. In the work by [95], the combination of ORB and PSO is employed, where PSO is initially used to search for the optimal coefficient, followed by the implementation of the ORB MPPT in the subsequent phase. This approach enhances efficiency without the need for wind speed measurement or pre-existing knowledge of parameters, making it a sensorless and parameter-free hybrid method. Another MPPT algorithm, incorporating a combination of PSF, PSO and other control techniques, proves effective in enhancing efficiency across all the speed range of the wind turbine [96].

In addition to employing a controller, there exist numerous optimization techniques aimed at refining its performance by minimizing a specified cost function. These techniques encompass a variety of algorithms inspired by biological or natural phenomena. Notable examples include the Dandelion optimization algorithm (DOA), firefly optimization algorithm (FOA), lung performance-based optimization algorithm (LPOA), Genghis Khan Optimization Algorithm (GKSOA), Geyser-inspired optimization algorithm (GIOA), Prairie Dog optimization algorithm (PDOA), Dwarf Mongoose optimization algorithm (DMOA), and Gazelle optimization algorithm (GOA).

DOA is a nature-inspired optimization technique that mimics the dispersal mechanism of dandelion seeds. It uses probabilistic movements to explore solution spaces efficiently, balancing between exploration and exploitation to find optimal solutions to optimization problems [97]. FOA is a nature-inspired optimization method based on the flashing behavior of fireflies. It uses the brightness of fireflies to represent the quality of potential solutions. Fireflies are attracted to brighter ones, which correspond to better solutions. Through iterative movement toward brighter neighbors and random exploration, FOA efficiently searches for optimal solutions in optimization problems [98]. LPOA is an optimization technique inspired by respiratory systems. It dynamically regulates exploration and exploitation in optimization processes. LPOA adapts principles from lung performance to enhance solution search efficiency, ensuring a balance between exploration and exploitation for optimal solution discovery [99]. GKSOA is a metaheuristic optimization method inspired by strategic conquest tactics employed by Genghis Khan. It emphasizes dynamic adaptation and resource allocation to optimize the search for solutions in various optimization problems [100].

GIOA is an optimization method that mimics the eruptive patterns of geysers. It balances exploration and exploitation in the search for optimal solutions by leveraging the natural phenomenon of geyser eruptions [101]. PDOA is an optimization technique inspired by the cooperative foraging behavior of prairie dogs. It promotes collaboration and information exchange among individuals in the optimization process to enhance solution search efficiency and convergence [102–104]. DMOA is an optimization approach inspired by the social dynamics and cooperative hunting strategies observed in dwarf mongoose communities. It emphasizes collaboration among individuals to enhance solution refinement and convergence in optimization problems [105, 106]. GOA is an optimization method inspired by the evasive maneuvers and swift decision-making of gazelles in evading predators. It promotes adaptability and robustness in dynamic environments by incorporating strategies similar to those used by gazelles to find optimal solutions in various optimization problems [107, 108].

2.5.5 Hybrid fractional-order-intelligent algorithms

This involves combining fractional-order (FO) control techniques with intelligent algorithms to optimize the MPPT capabilities of a wind energy system. Fractional-order control employs fractional calculus in control system design. Unlike traditional MPPT algorithms, which often use integer-order derivatives and proportional-integral (PI) controllers, fractional-order calculus involves derivatives and integrals with non-integer orders (such as 1.5 or 2.5). This provides additional flexibility and improved performance in certain applications, enabling more accurate modeling and control of dynamic systems [73, 109].

One of the key benefits of intelligent-fractional-order MPPT algorithms is their adaptability to varying wind conditions. They can continuously adjust the control variables, such as rotor speed or pitch angle, to track the changing optimal operating point, thereby maximizing energy extraction. These algorithms aim to improve the overall efficiency and energy yield of wind turbines by reducing losses and increasing the conversion efficiency of wind energy into useful output power. Essential features of fractional-order control include flexibility and superior performance. Intelligent algorithms inherently possess the capability for adaptability and optimization. Consequently, the integration of fractional order with intelligent algorithms results in a performance characterized by heightened adaptability, improved robustness, and optimized efficiency [36, 110].

Intelligent fractional-order MPPT algorithms may be computationally more demanding than simpler integer-order control strategies. However, they have the potential to provide higher efficiency and better performance, especially in wind farms with complex, turbulent wind patterns [110–112]. These algorithms are an area of active research and development in the field of wind energy. Researchers are continually working to improve the accuracy and efficiency of MPPT algorithms through the integration of fractional-order calculus and intelligent techniques [113–116].

Table 5 presents a comparison of the characteristics of various hybrid MPPT control algorithms, and a compilation of references for MPPT algorithms is listed in Table 6.

3 Comparative analysis and discussion

After reviewing various literature sources, a comparative analysis was conducted, considering factors such as adaptability, susceptibility, robustness, efficiency, convergence speed, sensor usage, complexity, reliance on prior knowledge, and overall cost. The results of this analysis are presented in Tables 1, 2, 4, and 5. Table 3 specifically delves into the comparison between conventional MPPT algorithms and their modified counterparts. The primary objective of an MPPT algorithm in a WECS is to optimize the output power of a variable wind turbine system. Selecting an appropriate MPPT algorithm proves to be a challenging task.

When assessing IPC MPPT algorithms like TSR, PSF, and OTC, their notable attributes include speed and simplicity. However, it is essential to highlight that these algorithms prioritize maximizing captured mechanical wind power rather than optimizing electrical power output. As indicated by the data in Table 1, both TSR and PSF mandate the use of a wind speed sensor. TSR, in particular, demonstrates superior efficiency compared to PSF and has the added advantage of not requiring training and memory. Nevertheless, the incorporation of a speed sensor anemometer, which is both costly and adds an extra expense to the system, presents a challenge. The real-time application of these techniques is further complicated by the significant difference in wind velocity near the turbine compared to the free stream velocity. The OTC MPPT algorithm is recognized for its simplicity, fast, and efficiency, and it does not require a wind speed measurement. Nonetheless, due to its indirect measurement of wind speed, changes in wind speed may not be promptly and prominently reflected in the reference torque. This particular aspect diminishes OTC efficiency when compared to the TSR algorithm. In terms of the PSF and OTC algorithms, their performance and complexity are comparable, especially regarding training requirements. They collectively offer a cost-effective control solution for WECS. Table 1 shows a comparison of the characteristics of IPC algorithms.

Table 2 provides an overview of the characteristics of DPC MPPT algorithms, such as P&O, INC, and ORB. These algorithms are widely valued for their simplicity, allowing for the direct computation of optimal electrical power without the necessity for advanced knowledge or wind speed mea-

Table 5 Comparison of the characteristics of hybrid MPPT algorithm [30, 36, 38, 47, 52, 54, 77, 117]

MPPT algorithm features	Hybrid conventional	Hybrid conventional-intelligent	Hybrid intelligent	Optimization based hybrid	Hybrid fractional-order-intelligent
Adaptability	Average	Excellent	Excellent	Excellent	Excellent
Computational complexity	Easy	Intermediate	Greater	Greater	Greater
Efficiency	Intermediate	Superior	Superior	Superior	Very superior
Oscillation	Depends	Depend on the algorithms	Absent	Absent	Absent
Overall expense	Average	Expensive	Expensive	Expensive	Expensive
Robustness	Relatively robust	Robust	Very robust	Very robust	Very robust
Speed of convergence	Intermediate	Intermediate	Fast	Fast	Very Fast
Storage	Depends	Present	Present	Present	Present
Time response	Depends	Relatively fast	Fast	Fast	Very Fast
Wind speed measurement	Depends	Depends	Depends	Depends	Depends
Wind turbine characteristics	Depends	Not mandatory	Not mandatory	Not mandatory	Not mandatory

Table 6 A compilation of references on MPPT algorithm for WECS

MPPT algorithm	References	Remarks
MPPT algorithms	[30, 38, 42, 44, 51, 52]	The papers discuss various MPPT control techniques for WECSs, analyzing the advantages and disadvantages of each based on different parameters and applications. The evaluations provide insights into the specific strengths and limitations of these algorithms in diverse contexts, offering a comprehensive overview of their effectiveness in WECS
Modified TSR	[64, 118, 119]	Presented is an MPPT algorithm based on modified TSR, which includes the development of an algorithm for estimating wind speed. This modified approach is then contrasted with conventional TSR-based algorithms
Modified P&O	[32, 38, 58, 58, 59, 120, 121]	A comprehensive review that encompasses both conventional and modified P&O techniques for MPPT is presented. The review delves into the nuances of traditional P&O methods and explores the advancements achieved through modifications
Intelligent (FLC)	[122–124]	FLC-based MPPT algorithm is presented, and its performance in tracking the maximum power is discussed
Intelligent (NN)	[70, 76, 86]	These papers introduce an MPPT algorithm based on Neural Networks (NN), and its ability to track the maximum power is thoroughly examined and discussed
Intelligent (NN)	[82, 125]	Introducing an MPPT algorithm based on Neural Networks (NN), these research studies highlight its superior capability in tracking maximum power compared to other MPPT controllers, even though they require data for training
Intelligent (NN,FLC)	[71]	FLC and NN based MPPT are presented and evaluated in diverse environmental conditions using MatLab/SIMULINK
Hybrid (FLC&NN)	[31]	In this article, hybrid neural network and fuzzy logic control is introduced and discussed its performance
Hybrid (P&O and FLC)	[35, 76]	Hybrid P&O and PSF based MPPT algorithm is discussed. This proposed techniques applied their individual advantages and improve overall performance of the system
Hybrid (PSF and PSO)	[96]	Hybrid PSF-based MPPT algorithm with PSO optimization method is presented and its performance is discussed

Table 6 continued

MPPT algorithm	References	Remarks
Hybrid (P&O and ORB)	[60, 95]	Hybrid P&O and ORB method is presented. Drawbacks and benefits of individual algorithms are discussed. To address their limitations, a hybrid algorithm is proposed and its advantages are discussed
Hybrid (P&O and OTC)	[126]	Hybrid P&O and OTC MPPT algorithm is presented. The algorithm is tested under various wind conditions, demonstrating its adaptation capability and improved energy efficiency
Fractional-order-intelligent	[112, 113]	An MPPT algorithm, combining fractional-order (FO) and intelligent elements, is introduced and its performance is compared with that of classical controllers
Intelligent	[30, 36, 38, 44, 51]	Various intelligent MPPT algorithms are discussed, and their merits, demerits, and applications are explained
Hybrid	[30, 38, 40]	The study outlines the analysis of multiple hybrid control techniques and their specific drawbacks. Furthermore, the benefits of combining two or more MPPT algorithms are explained, with the objective of improving overall performance

surements. This straightforward approach not only enhances their cost-effectiveness but also contributes to their overall reliability. Both the P&O and INC algorithms are crafted with minimal memory requirements. In terms of power efficiency, the INC method theoretically has the capacity to achieve more effective tracking of the MPP than the P&O algorithm. Despite the shared merits of straightforward design and adaptability in both algorithms, the existence of fluctuations around the MPP can potentially diminish the performance of the wind energy system. To enhance MPPT efficiency, accelerate convergence speed, and improve system precision, a customized INC algorithm is employed. This adjusted algorithm automatically adjusts the step size to accurately trace the MPP of the wind energy system.

The accuracy of the ORB MPPT algorithm is apparent, relying solely on measurements of DC voltage and current. Noteworthy is its autonomy and adaptability, as it operates without the need for preexisting knowledge of the system or wind speed sensors. Additionally, it excels in precision and effectiveness when tracking maximum wind power. However, in terms of expense, a comparison with other algorithms in Table 2 suggests that this specific algorithm is slightly more expensive.

Intelligent algorithms optimize a wind turbine operation and extract the maximum power through sophisticated control strategies employing advanced computational methods. Currently, a diverse range of intelligent control methods is extensively employed, including expert control, fuzzy control, neural network control, and optimization algorithms such as GA, ACO, PSO, among others. These algorithms are specifically designed to enhance the efficiency and overall performance of the MPPT system, especially in scenarios with stochastic and unpredictable wind speeds. They find common application in various complex controlled systems, addressing intricate challenges associated with highly nonlinear and uncertain control issues in complex systems. Intelligent algorithms prove invaluable in solving problems traditionally difficult to resolve using conventional methods with superior performance. However, they required enough data and analysis for effective practical implementation. Table 4 provides a comparison of performance characteristics among intelligent algorithms.

The multivariable P&O is a control strategy derived from P&O algorithm, but it is expanded to optimize several variables concurrently. This principle entails adjusting and optimizing multiple variables, commonly the currents of various generators within a wind turbine system, with the goal of collectively maximizing power output. The overarching objective is to improve the efficiency of energy capture by systematically perturbing the pertinent variables and observing their influence on the overall system performance. ISMPPT algorithms are techniques specifically developed to improve the operation of a wind turbine system without depending on direct sensor measurements. Instead of relying on sensors, these algorithms employ mathematical models, estimators, or adaptive control strategies to deduce or estimate the essential parameters crucial for optimizing the turbine's performance, all without directly utilizing sensor measurements.

The intricacies of energy conversion in nonlinear wind power systems stem from the unpredictable and stochastic nature of wind speed. Relying solely on a single control method often proves limiting and falls short of achieving desired outcomes due to inherent uncertainties. To address these challenges, hybrid approaches have emerged, enhancing overall control effectiveness and introducing adaptability. In the context of wind energy, a hybrid MPPT algorithm integrates various methods, aiming to boost adaptability and improve overall efficiency and robustness as shown in Table 5. Each MPPT algorithm brings its unique strengths and weaknesses, and the hybrid strategy strategically capitalizes on these in different conditions, ensuring adaptability to diverse scenarios.

The hybrid fractional-order-intelligent MPPT algorithm, specifically tailored for wind energy, epitomizes a cohesive control approach that amalgamates the advantages of fractional-order control techniques with intelligent algorithms. This integrated strategy seeks to surpass the limitations of conventional and other hybrid methods, aiming to enhance adaptability and elevate the overall efficiency of wind energy systems by optimizing power extraction from the wind. Moreover, within the landscape of hybrid MPPT algorithms, the fractional-order-intelligent MPPT algorithm currently stands out as a prominent focus in ongoing research.

4 Future directions

A wind energy system is a renewable energy solution that converts the kinetic energy of the wind into usable energy. To efficiently extract maximum power and maintain control over the system, a controller is essential. However, due to the unpredictable and stochastic nature of the wind, an effective control algorithm is required. This algorithm should possess qualities such as adaptability to changing environmental conditions (wind speed and direction), robustness, high efficiency, accuracy, and intelligence. In WECS, intelligent-based MPPT algorithms, including intelligent algorithms, hybrid intelligent algorithms, and hybrid fractional-order intelligent algorithms, are preferred. These algorithms have demonstrated significant improvements in the efficiency, accuracy, adaptability, and overall performance of wind energy conversion systems.

Based on this review paper, the forthcoming research on MPPT for wind energy systems is expected to primarily focus on three key areas: hybrid intelligent algorithms, hybrid fractional-order intelligent algorithms, and hybrid fractional-order intelligent algorithms coupled with optimization techniques. This underscores the current emphasis in renewable energy systems, which present distinct advantages over alternative approaches.

5 Conclusion

To improve the efficiency of a wind power generation in the face of unpredictable wind conditions, the selection of a suitable MPPT algorithm is paramount. In this paper, a comprehensive overview is conducted, entailing a comparative analysis of diverse MPPT algorithms. The review facilitates the identification and selection of the most suitable MPPT algorithm for a specific application, thereby improving system performance and maximizing overall output power. The MPPT algorithms are classified into four primary groups: IPC, DPC, intelligent, and hybrid algorithms, each presenting distinctive advantages and disadvantages.

Conventional algorithms display drawbacks, including slow convergence speed, the necessity for prior knowledge, dependence on wind speed measurements, and low efficiency in power tracking. The conventional perturb and observe algorithm, among conventional MPPT algorithms, stands out for its simplicity and cost-effectiveness, making it a preferred choice for achieving the MPP. However, accurately selecting the required step-size poses a significant challenge for CPO directly influenced by factors such as settling time and oscillations around the MPP. As a result, MPO algorithms have been introduced to address these limitations by incorporating fixed, adaptive, variable, and hybrid step-sizes. MPO based on hybrid step-sizes exhibits enhanced performance, albeit introducing added complexity due to the generation of different step-sizes. MPO based on hybrid step-sizes exhibits enhanced performance, although it introduces added complexity due to the generation of different step-sizes.

In the domain of intelligent MPPT algorithms, developments such as fuzzy logic, neural networks, and diverse expert controls have been employed to optimize the efficiency of wind energy conversion. These intelligent MPPT algorithms excel in extracting maximum power efficiently, notwithstanding their requirement for a substantial amount of data to operate effectively. The application of optimization methods such as PSO, GA, and ACO in hybridization has resulted in notable enhancements for quickly identifying the optimal operating point of a system. This has led to improved precision in MPP tracking and increased efficiency in energy conversion. The success of the conventional-intelligent hybrid approach is especially evident in reducing the control method's reliance on system parameters and the necessity for wind speed measurements, ultimately contributing to enhanced overall efficiency. Intelligent hybrid algorithms, exemplified by fuzzy logic control-neural network (FLC-NN), not only tackle the limitations of MPPT but also bolster the resilience and overall effectiveness of the algorithm. Moreover, we assess the hybrid fractional-order-intelligent approach for its outstanding tracking capabilities, especially in conditions characterized by complexity, variability, and challenging-to-predict wind patterns. This method offers enhanced adaptability, increased robustness, and optimized performance. Ongoing research in this domain explores synergies between fractional-order control and intelligent algorithms, aiming to advance and adapt control strategies for WECSs.

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Declarations

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