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RESEARCH ARTICLE-ELECTRICAL ENGINEERING

Enhanced Stability and Performance of the Tidal Energy Conversion System Using Adaptive Optimum Relation-Based MPPT Algorithms

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Abstract

Tidal energy is a highly predictable and sustainable resource with significant potential to meet global energy demands. This study proposes an adaptive optimum relation-based (A-ORB) maximum power point tracking algorithm to enhance the efficiency, stability, and adaptability of tidal energy conversion systems. The A-ORB algorithm integrates the optimum relation-based (ORB) approach with Hill Climb Search (HCS), along with an adaptive gain adjustment mechanism that dynamically tunes the parameter K based on power variation (ΔP). This hybrid strategy enables faster convergence, improved responsiveness to tidal fluctuations, and reduced power oscillations. The novelty of the proposed method lies in the combination of ORB and HCS with adaptive gain tuning, which collectively improves MPPT performance under variable tidal conditions. Simulation results show that A-ORB outperforms conventional techniques such as small step perturb and observe (SS-PO), small step incremental conductance (SS-InC), and bio-inspired particle swarm optimization (BI-PSO) in both tracking accuracy and power output. Specifically, A-ORB achieves a convergence time of 0.32 s and a maximum power output of 4833 W, compared to 4658 W (0.41 s) for SS-PO, 4561 W (0.5 s) for SS-InC, and 4699 W (0.37 s) for BI-PSO. Moreover, A-ORB exhibits significantly lower power oscillations (3.9 W) compared to 17.88 W (SS-PO), 21.96 W (SS-InC), and 10.4 W (BI-PSO). These findings demonstrate the potential of A-ORB to enhance MPPT efficiency, reduce transient response time, and improve adaptability in dynamic tidal energy environments.

Keywords Optimum relation based (ORB) · Tidal energy conversion system (TECS) · Maximum power point (MPP) · Maximum power point tracking (MPPT)

1 Introduction

The ongoing depletion of fossil fuels, coupled with the harmful environmental impact of CO_2 emissions, has intensified global interest in renewable energy sources such as wind, solar, and ocean energy [1, 2]. Among these alternatives, ocean energy, including tidal, wave, and ocean thermal energy, stands out for its high predictability and stability, making it a promising option for large-scale power generation [3, 4].

Tidal energy is a highly predictable renewable resource with substantial potential to meet global energy demands. Unlike wind and solar energy, which are subject to weather variability, the consistent nature of tidal energy simplifies grid integration and reduces dependency on energy storage solutions, thereby enhancing its viability as a long-term renewable alternative [5, 6]. Nevertheless, despite these advantages, efficiently harnessing power from variable tidal flows remains a major challenge in tidal energy conversion systems (TECS), often leading to suboptimal turbine performance [7, 8].

To address this challenge, a variety of maximum power point tracking (MPPT) algorithms have been developed to enhance the efficiency and stability of TECS. MPPT techniques dynamically adjust the operating point to maximize power extraction, ensuring optimal system performance under fluctuating tidal conditions [9]. In this study, we propose an adaptive optimum relation-based (A-ORB) MPPT algorithm that integrates the optimum relation-based (ORB) approach with Hill Climb Search (HCS) to improve tracking performance in dynamic tidal environments. Furthermore,

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an adaptive gain factor adjustment mechanism is introduced, wherein the gain factor K is dynamically tuned based on power variations (ΔP), enabling faster convergence and enhanced stability. The outcome of this study is an improved MPPT algorithm that achieves a convergence time of 0.32 s and a maximum power output of 4833 W, significantly outperforming conventional methods while reducing power oscillations to just 3.9 W.

MPPT techniques have been widely investigated in renewable energy systems, particularly in photovoltaic (PV) and wind energy applications. However, their application in tidal energy conversion systems (TECS) remains relatively underexplored. Existing MPPT methods often encounter significant challenges when operating under the dynamic and nonlinear conditions characteristic of tidal environments. Despite progress in both conventional and intelligent MPPT algorithms, their performance in tidal energy systems is often limited by issues such as oscillatory behavior, high computational complexity, sensor dependency, and sensitivity to parameter variations [10].

Several studies have emphasized the limitations of conventional MPPT techniques. The perturb and observe (P&O) algorithm, though widely used for its simplicity, exhibits significant oscillations around the maximum power point (MPP), which leads to decreased overall efficiency [11]. Additionally in [12], it was reported that P&O struggles to balance convergence speed and stability, rendering it less suitable for environments with rapidly changing tidal speeds. The tip speed ratio (TSR) method, while effective under steady-state conditions, depends heavily on accurate sensor measurements of turbine speed and tidal velocity. In real-world TECS applications, however, sensor inaccuracies and transmission delays often impair the algorithm's tracking performance, ultimately reducing system reliability [10].

To overcome these limitations, intelligent MPPT approaches have been proposed to enhance adaptability and tracking performance. Fuzzy logic control (FLC) and artificial neural networks (ANN) have demonstrated effectiveness in handling nonlinearities [13] and dynamic conditions [14]. FLC offers robust performance but requires meticulous tuning to achieve optimal results [15], while ANN utilizes historical data for accurate MPP prediction but demands significant computational resources [16]. Metaheuristic optimization techniques, such as particle swarm optimization (PSO), provide global search capabilities and adaptability; however, they may encounter convergence challenges [17, 18]. Other optimization methods, including genetic algorithms (GA) [19] and the gray wolf optimizer (GWO) [20], have been explored for their optimization capabilities, though they often come at the cost of increased complexity or computational overhead [21].

Hybrid MPPT algorithms integrate conventional and intelligent methods to capitalize on their respective strengths while mitigating individual limitations. For example, PSO-incremental conductance (PSO-InC) has demonstrated enhanced convergence rates and tracking accuracy compared to standalone techniques [22]. However, such hybrid approaches often face challenges like increased computational burden, which can hinder their real-time applicability in dynamic tidal environments. Similarly, ORB-ANN has shown strong adaptability to varying conditions [23], but its dependence on extensive prior training reduces its effectiveness when sudden parameter changes occur.

A promising alternative is the optimum relation-based (ORB) MPPT algorithm, which has demonstrated a fast tracking response and stable performance in wind energy systems [21, 24]. However, its application in tidal energy systems remains largely unexplored. The ORB MPPT technique relies on predefined relationships between system parameters such as rotational speed, power output, converter DC voltage, and DC current, to reach the maximum power point (MPP) [16, 25]. Although effective under stable operating conditions, this dependency limits its adaptability in dynamic tidal environments, where fluctuations in water velocity and loading conditions are often unpredictable [26]. To overcome this limitation, the present study proposes an adaptive ORB approach aimed at improving both stability and performance in tidal energy systems. By reducing reliance on static system characteristics, the proposed method enhances the practicality and robustness of ORB-based MPPT under highly variable tidal conditions.

While MPPT techniques have been extensively studied in wind and solar energy systems, their application in tidal energy remains relatively underexplored. Given ORB's fast tracking response and inherent stability, it holds significant potential for addressing challenges in tidal energy systems, such as fluctuating currents and nonlinear parameter relationships. This study investigates the applicability of ORB in tidal energy by comparing its performance against conventional and intelligent MPPT algorithms and identifying areas requiring enhancement. Future research could incorporate economic evaluations, including exergoeconomic analysis and payback period calculations, to further assess the practical feasibility of the proposed approach. To emphasize existing research gaps, Table 1 presents a comparative analysis of various MPPT algorithms based on convergence speed, computational complexity, dependence on wind/water speed measurements, and prior training requirement.

Table 2 categorizes both previous and current studies on MPPT methods, highlighting the evolution of these techniques along with their respective limitations. Conventional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (InC), are valued for their simplicity but are hindered by issues such as oscillations around the Maximum Power Point (MPP) and slow convergence. Intelligent and hybrid approaches, including Fuzzy Logic

Table 1 Comparison of different MPPT techniques

MPPT techniques	Speed of convergence	Complexity	Speed measurement	Prior training
P&O	Varies	Low	No	No
InC	Low	Low	No	No
TSR	Fast	Low	Yes	No
OTC	Fast	Low	No	Yes
ORB	Fast	Low	No	No
FLC	Medium	High	Varies	Yes
ANN	Medium	High	Varies	Yes
Metaheuristic	Medium	High	Varies	No
Hybrid	Fast	Medium	No	No

Control (FLC) and Particle Swarm Optimization (PSO), offer improved tracking accuracy and adaptability; however, they often come at the cost of increased computational complexity and dependence on precise parameter tuning. Although the ORB MPPT algorithm has demonstrated effectiveness in wind energy applications, its application and potential benefits within tidal energy systems remain largely unexplored.

Several studies have explored MPPT techniques in real-world applications across various renewable energy systems. For example, a study in [27] investigated an improved P&O method for photovoltaic (PV) systems, achieving high efficiency but encountering significant power oscillations. Similarly in [28], proposed a modified P&O algorithm for wind energy systems, which demonstrated high tracking accuracy, albeit with increased algorithmic complexity. In another study, [22] introduced a hybrid PSO-InC MPPT approach for wind energy applications, resulting in enhanced tracking speed and reduced oscillations. Within the context of tidal energy conversion systems (TECS), a research in [29] developed a hybrid FLC-ORB method that effectively mitigated oscillations but introduced moderate complexity due to the integration of the fuzzy logic component.

These studies provide valuable benchmarks for assessing the performance of the proposed A-ORB MPPT algorithm. The A-ORB approach harnesses the advantages of intelligent MPPT strategies such as enhanced tracking speed and efficiency, while minimizing computational complexity and sensitivity to parameter variations. Unlike existing methods, A-ORB incorporates an adaptive control strategy that dynamically optimizes performance in response to variations in tidal flow and load conditions. To address the identified gaps, this study introduces the A-ORB MPPT algorithm, aimed at improving system stability and performance under dynamic tidal environments, without compromising computational efficiency. The key contributions of this study are as follows:

1. A novel hybrid MPPT strategy is proposed by integrating the optimum relation-based (ORB) method with Hill Climb Search (HCS) to enhance tracking performance under varying tidal conditions. This hybridization improves the algorithm's capability to manage dynamic tidal flow variations and optimize power extraction.
2. An adaptive gain factor adjustment mechanism is introduced, wherein the gain factor K is dynamically tuned based on power variations (ΔP). This adaptive approach improves convergence speed and ensures faster and more stable tracking of the maximum power point (MPP).
3. The proposed A-ORB MPPT algorithm is extensively evaluated and benchmarked against widely used MPPT techniques, including small step perturb and observe (SS-PO), small step incremental conductance (SS-InC), and bio-inspired particle swarm optimization (BI-PSO), demonstrating superior efficiency and faster convergence.
4. The algorithm's adaptability to sudden changes in tidal velocity is validated through simulation, exhibiting quicker transient recovery and significantly reduced power oscillations.

The remainder of this paper is organized as follows: Sect. 2 presents the modeling of the tidal energy system and the implementation of the proposed MPPT algorithm. Section 3 provides an in-depth analysis of the simulation results, including performance comparisons. Finally, Sect. 4 concludes the study with key findings, identified limitations, and suggestions for future research.

2 System Overview

Figure 1 illustrates the schematic diagram of the simulated TECS. The system consists of a tidal turbine-driven permanent magnet synchronous generator (PMSG), which is connected to the load through an uncontrolled rectifier and a DC-DC boost converter.

Table 2 Comparison of existing MPPT studies and the proposed A-ORB method for tidal energy systems

MPPT technique	Algorithm type	Application in TECS	Adaptability to parameter variations	Hybrid approach	Key weaknesses	Research gap addressed	How proposed A-ORB overcomes these limitations
P&O	Conventional	Yes	Low	No	Oscillations around MPP	Stability issues with steady-state oscillations [11]	A-ORB minimizes oscillations through adaptive control
InC	Conventional	Limited	Moderate	No	Trade-off between speed & fluctuation	Slow tracking in dynamic conditions [30]	A-ORB improves stability and convergence efficiency
TSR	Conventional	Yes	Low	No	Dependence on sensor accuracy	High sensitivity to sensor errors [10]	A-ORB reduces reliance on sensors through adaptive control
FLC	Intelligent	Yes	Moderate	No	Requires careful tuning	Complexity in parameter tuning [31]	A-ORB minimizes tuning effort using adaptive learning
PSO	Intelligent	Yes	Moderate	No	Computational complexity	High processing requirements [32]	A-ORB lowers computational complexity while maintaining adaptability
ORB	Conventional	No	Low	No	System parameter dependency	Performance affected by system variations [26]	A-ORB enhances adaptability to system variations
BI-PSO	Hybrid	No	Moderate	Yes	High complexity	Balancing complexity and efficiency trade-offs	A-ORB optimizes performance while balancing complexity
Proposed A-ORB	Hybrid	Yes	High	Yes	–	Overcomes system parameter dependency in TECS	Ensures high adaptability, efficiency, and stability in tidal systems

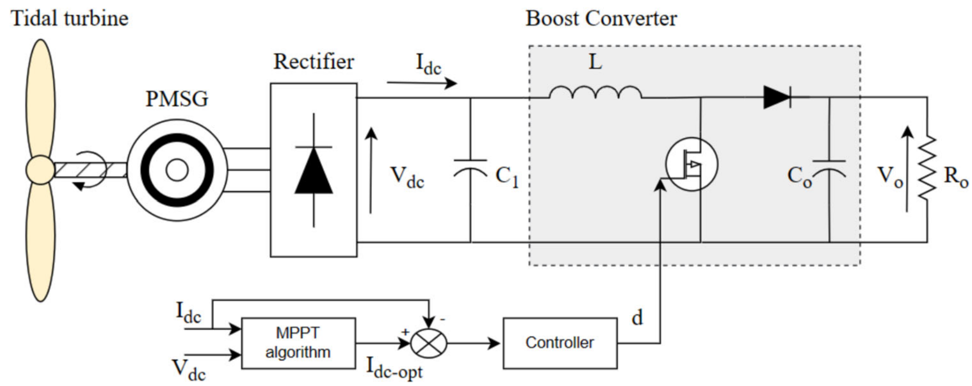

Fig. 1 Block diagram of simulated tidal turbine-based PMSG

2.1 Tidal Turbine Characteristics

The input power to the tidal turbine is derived from the rotational force exerted by tidal currents. The mechanical power generated by a tidal turbine is expressed by the following equation [33]:

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

where:

P_m (W): Mechanical power output of the turbine.

$C_p(\lambda, \beta)$ (unitless): Power coefficient, representing the efficiency of the turbine.

$\rho = 1025$ kg/m^3: Water density.

R (m): Turbine rotor radius.

V (m/s): Tidal velocity.

The power coefficient C_p is a nonlinear function influenced by the tip speed ratio λ and the blade pitch angle β. It can be expressed as follows [34]:

$$C_p(\lambda, \beta) = C_1\left(\frac{C_2}{\lambda_1} - C_3\beta - C_4\right)e^{-\frac{C_5}{\lambda_1}} + C_6\lambda \tag{2}$$

$$\frac{1}{\lambda_1} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{3}$$

$$\lambda = \frac{\omega_r R}{V} \tag{4}$$

where:

λ (unitless): Tip speed ratio, defined as the ratio of the blade tip speed to the tidal current speed.

ω_r is rotational speed.

β (degrees): Blade pitch angle.

$C_1 = 0.5176$, $C_2 = 116$, $C_3 = 0.4$, $C_4 = 5$, $C_5 = 21$, $C_6 = 0.0068$: Turbine specific constants.

The exponential term $-\frac{C_5}{\lambda_1}$ accounts for the diminishing returns of Cp at high λ values, ensuring a realistic power coefficient curve.

Figure 2 illustrates the Simulink model of the tidal turbine subsystem block, developed based on the given tidal turbine characteristics.

Figure 3 illustrates the C_p versus λ characteristics of the tidal turbine. For the simulated tidal turbine in this study, the optimal λ (λ_{opt}) is 8.1, corresponding to a maximum Cp (C_{p_max}) of 0.48. C_{p_max} value is achieved when λ is optimized. Maintaining λ at its optimal value ensures that extracted energy remains at its highest operating point.

The tidal velocity must exceed 2.25 m/s to achieve realistic power output, particularly with a larger blade area and high rotational speed [35]. The rotor radius for a 6-kW turbine is determined using Eq. (1), assuming $Cp = 0.48$:

$$P_m = \frac{1}{2} C_p(\lambda, \beta) \rho \pi R^2 V^3$$

Substitute the known values:

$$6000 = \frac{1}{2}(0.48)(1025)\pi R^2(2.5)^3$$

Solve for R^2:

$$R^2 = \frac{6000}{12075.49} = 0.497m^2$$

$$R = \sqrt{0.497} = 0.7m$$

Hence, a turbine with a 0.7 m rotor radius is suitable for extracting 6 kW of power at a tidal velocity of 2.5 m/s.

2.2 Conventional ORB MPPT Algorithm

The conventional optimum relation-based (ORB) MPPT algorithm is a structured approach designed to identify the maximum power point (MPP) in tidal energy systems. It utilizes mathematical models that define the relationships between key system variables, such as torque versus power, rectified DC voltage versus power, and DC current versus DC voltage [26], to compute an optimal coefficient (K_{opt}).

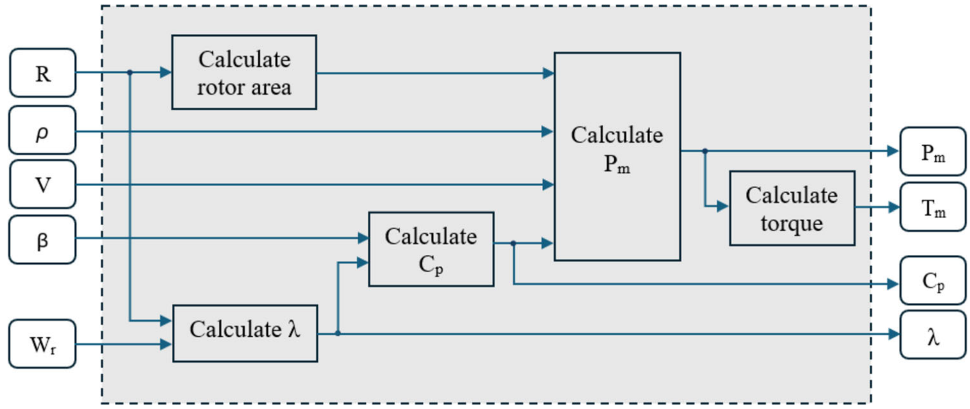

Fig. 2 Simulink model of tidal turbine

This coefficient, derived from peak voltage and current values, is used to estimate the reference current or duty cycle, ensuring the system operates close to the MPP. For example, the optimal current can be calculated as follows [36].

$$I_{\mathrm{dc(opt)}} = K_{\mathrm{opt}} V_{\mathrm{dc}}^2 \tag{5}$$

$$K_{\mathrm{opt}} = \frac{I_{\mathrm{dc(peak)}}}{V_{\mathrm{dc(peak)}}^2} \tag{6}$$

Although this algorithm is straightforward and performs well under stable conditions, it relies heavily on fixed system parameters. This dependency limits its adaptability to variations in tidal flow or turbine behavior, potentially causing oscillations or reduced power output.

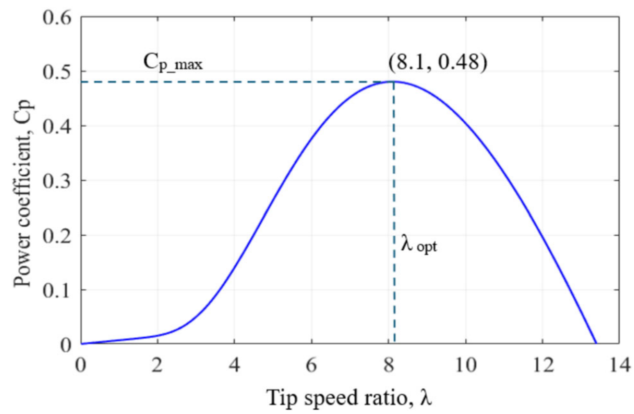

Fig. 3 C_p versus λ characteristics of the tidal turbine

2.3 Proposed Adaptive ORB (A-ORB) MPPT Algorithm

The proposed adaptive ORB (A-ORB) MPPT algorithm, as illustrated in Fig. 4, integrates the hill climb search (HCS) and optimum relation-based (ORB) methods, enhancing its adaptability to dynamic conditions. The algorithm begins by measuring the voltage and current, followed by the calculation of electrical power using $P_e = V_{dc} \times I_{dc}$. To determine system dynamics, the power variation (ΔP) and voltage variation (ΔV) are computed as follows:

$$\Delta \mathrm{P} = P_{(n)} - P_{(n-1)} \tag{7}$$

$$\Delta \mathrm{V} = V_{(n)} - V_{(n-1)} \tag{8}$$

Based on these variations, the algorithm selects the appropriate tracking mode. If ΔP exceeds a predefined threshold, the system enters HCS Mode, where the duty cycle is perturbed to track the MPP using a hill-climbing approach. Conversely, if ΔP falls below the threshold (*th*), the system switches to ORB Mode, which stabilizes the power extraction process. Within ORB mode, the algorithm applies an adaptive gain-based MPPT strategy to optimize power tracking while preventing oscillations. Unlike conventional ORB methods that use a fixed gain factor (K), the proposed method dynamically adjusts K based on real-time power variations, ensuring a balance between fast tracking and stability. The gain factor is initially set as K_{init} and is updated using the following relation:

$$\mathrm{K(n)} = \begin{cases} K(n-1) + a_1 \bullet |\Delta P|, \; if|\Delta P| > P_{\mathrm{th}} \\ K(n-1) - a_2 \bullet |\Delta P|, \; if|\Delta P| \le P_{\mathrm{th}} \end{cases} \tag{9}$$

where:

P_{th}: predefined threshold for power variation.

α_1 and α_2: adaptive tuning parameters for adjusting K.

If ΔP is large, K increases to accelerate MPP tracking, whereas a small ΔP decreases K to enhance system stability. After adjusting K, the algorithm computes the reference current using Eq. (6) and updates the converter duty cycle accordingly. A convergence check is then performed to ensure minimal power fluctuation around the MPP. If convergence is achieved, the algorithm terminates; otherwise, it continues iterating.

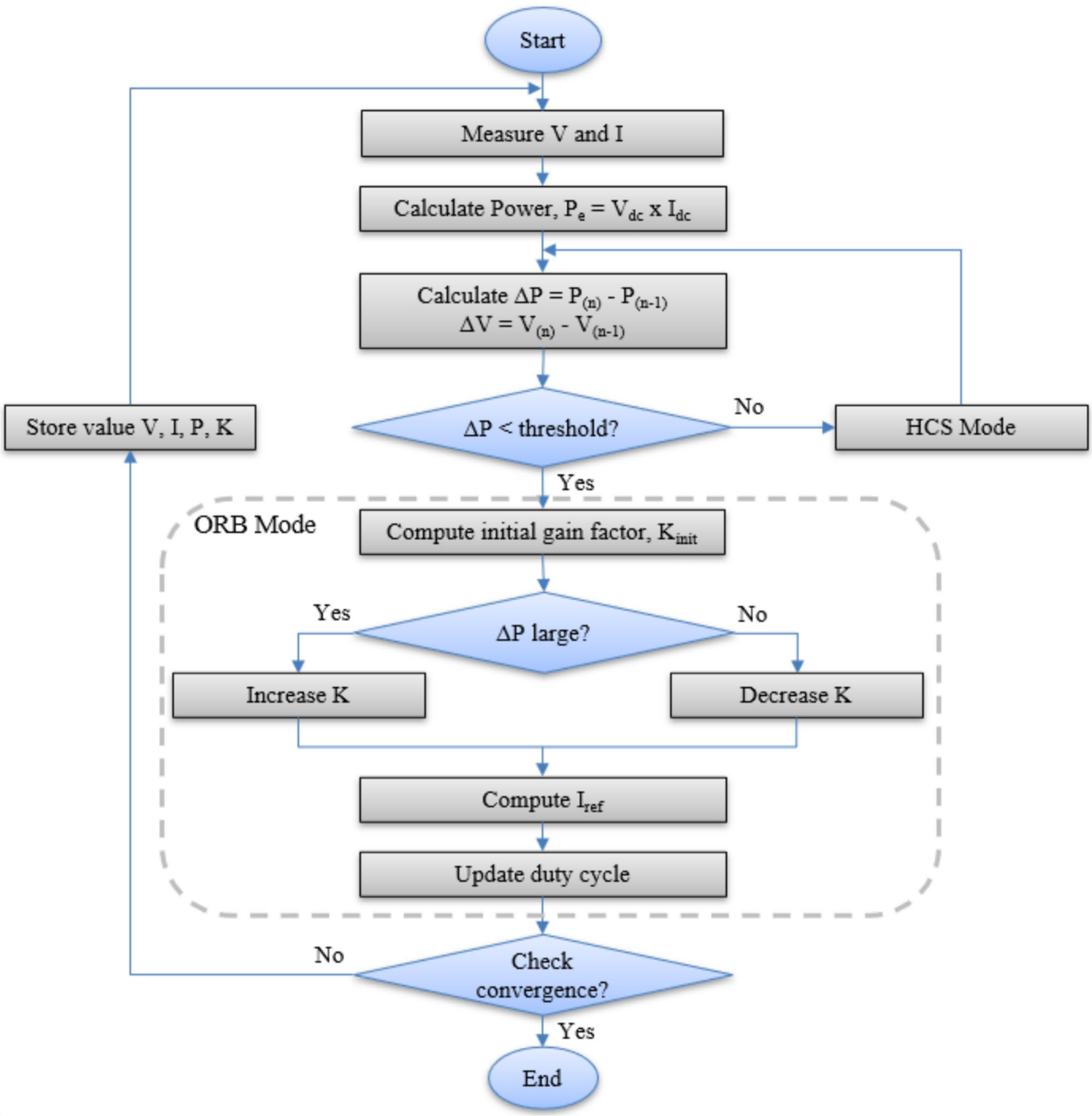

Fig. 4 The flow chart for the proposed A-ORB MPPT

The A-ORB MPPT algorithm introduces significant improvements over conventional MPPT techniques. The dynamic gain adaptation ensures faster convergence to the MPP while minimizing power oscillations. Additionally, the adaptive mechanism prevents excessive fluctuations around the MPP, enhancing energy extraction efficiency and reducing power losses.

2.4 Simulation Results and Discussions

Variable tidal velocities ranging from 2.25 to 3.25 m/s are used to evaluate the efficiency of the A-ORB MPPT algorithm, with its performance compared against conventional P&O and InC MPPT algorithms that employ small, fixed step sizes (SS-PO and SS-InC) as well as the Bio-Inspired PSO (BI-PSO). This section details the design, simulation tests, and performance comparisons conducted for SS-PO, SS-InC, BI-PSO, and A-ORB MPPT algorithms using the

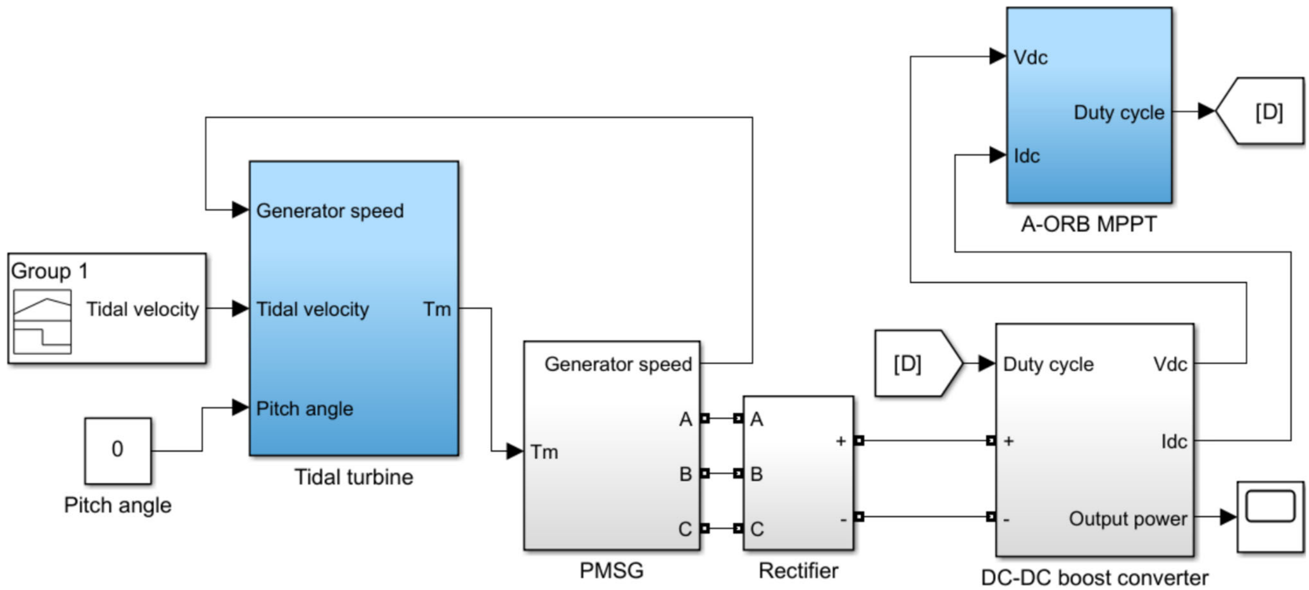

Fig. 5 Simulink model for the A-ORB MPPT algorithm

Table 3 Parameter setup for tidal turbine subsystem

Parameter	Value
Power coefficient, C_p	0.48
Water density, p	1025 kg/m^3
Water current speed, V	2.5 m/s
Turbine rotor radius, R	0.7 m
Rotor angular speed, W_r	28.93 m/s
Tip speed ratio, TSR	8.1
Output power, P_m	6000 W

Table 4 The calculated K_{opt} based on DC voltage and current

Tidal velocity (m/s)	DC voltage, V_{dc} (V)	DC current, I_{dc} (A)	Optimal parameter, K_{opt}
2.25	260.4	16.80	2.4772×10^{-4}
2.5	290.4	20.66	2.4499×10^{-4}
2.75	318	25.11	2.4834×10^{-4}
3.0	348	29.79	2.4601×10^{-4}
3.25	375.6	35.10	2.4877×10^{-4}

MATLAB/Simulink simulation environment. As illustrated in Fig. 5, the Simulink model of the proposed algorithm is presented. The parameters used in the simulation are provided in Table 3.

The rotor speed, mechanical torque, and tip speed ratio play a crucial role in optimizing turbine performance under varying tidal conditions. The output mechanical power of 6 kW demonstrates high efficiency, indicating near-optimal operation and validating the design and simulation approach. With a power coefficient (C_p) of 0.48, the turbine effectively converts tidal flow kinetic energy into mechanical energy. This high C_p underscores the turbine's well-optimized design and commercial viability. Efficient tidal turbines contribute to expanding renewable energy portfolios, reducing reliance on fossil fuels, and mitigating environmental impact. The results confirm the feasibility of deploying similar turbines in tidal-rich areas, highlighting their potential in renewable energy generation.

2.5 Simulation of ORB MPPT Algorithm

In this simulation, incorporating the mean tidal speed derived from the simulated tidal profile is essential for calculating the optimum power coefficient (K_{opt}). This approach effectively minimizes the nonlinear relationship between K_{opt} and tidal velocity. The recorded ideal voltage and current at a tidal velocity of 2.5 m/s are 290.4 V and 20.66 A, respectively, with a calculated K_{opt} value is 2.4499×10^{-4}. Table 4 presents a tabulation of corresponding values for tidal velocities ranging from 2.25 to 3.25 m/s.

The calculated K_{opt} values illustrate the relationship between tidal velocity and turbine performance. Each K_{opt} value highlights the turbine's efficiency under specific conditions, demonstrating its capability to optimize power extraction. As tidal velocity increases from 2.25 to 3.25 m/s, the

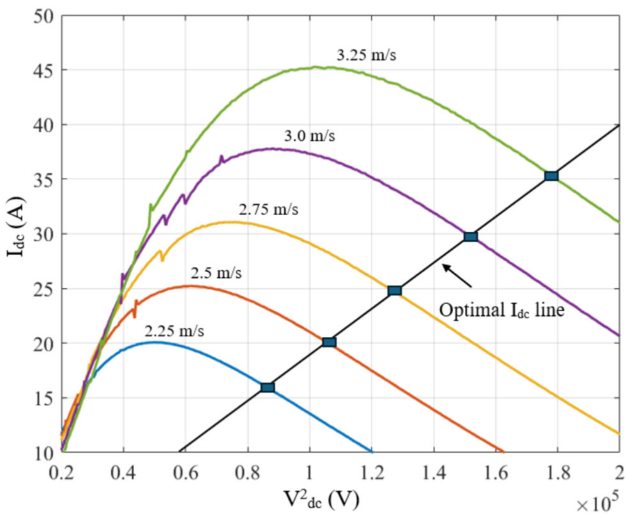

Fig. 6 Optimal I_{dc} line

corresponding DC voltage and DC current values increase significantly. For instance, at 3.25 m/s, the DC voltage reaches 375.6 V, and the DC current is 35.10 A. These values indicate that the turbine can effectively handle higher power outputs as tidal velocities increase.

Using the tidal velocities specified in Table 2, Fig. 6 illustrates the I_{dc} versus $V^2{}_{dc}$ curve for the simulated system in this study. The figure presents five points, each representing the optimal voltage and current for the corresponding tidal speeds. The graph depicts the ideal relationship between I_{dc} and $V^2{}_{dc}$ through the optimal I_{dc} line. Consistently operating along this optimal line ensures that the TECS maintains power extraction close to the optimum value, thereby enhancing overall efficiency.

To manage the complexities of unique tidal velocities that require distinct sets of coefficients, an adaptive ORB MPPT algorithm with self-tuning capabilities is implemented. This approach effectively addresses nonlinearities and ensures accurate performance metrics in the simulation. The self-tuning mechanism enables the system to dynamically adjust coefficients in response to varying tidal conditions, maintaining measurement reliability and accuracy.

2.6 Convergence Speed

The convergence speed determines how quickly the system adapts to changes and reaches the optimal operating point. In dynamic tidal conditions, where environmental parameters can change rapidly, the ability to swiftly adjust and track the MPP is crucial. Figure 7 demonstrates that the A-ORB MPPT algorithm achieves convergence in 0.32 s, significantly faster than BI-PSO (0.37 s), SS-PO (0.41 s), and SS-InC (0.5 s). Although the SS-InC MPPT algorithm exhibits a strong initial response, its ascent is slower and

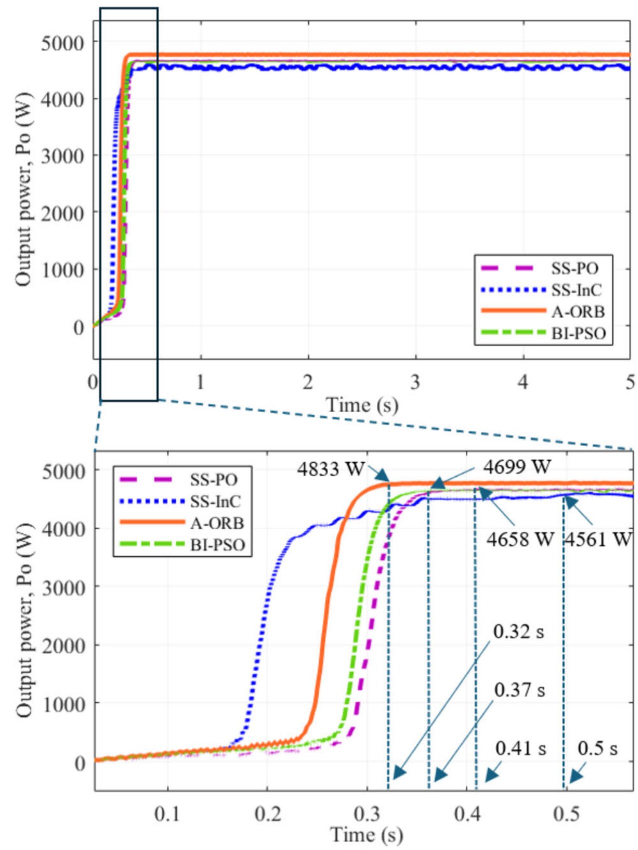

Fig. 7 Convergence speed for extracted output power

more prone to fluctuations as it approaches the MPP. Additionally, the A-ORB MPPT algorithm attains a maximum power output of 4833 W, surpassing BI-PSO (4699 W), SS-PO (4658 W), and SS-InC (4561 W). Achieving a higher maximum power output directly translates to greater energy capture, leading to increased electricity generation under the same conditions and enhancing the overall efficiency and effectiveness of the tidal energy extraction system.

The combined advantage of faster convergence and higher power output, as similarly observed in [37], significantly enhances the system's responsiveness. Faster adjustments to the optimal power point reduce the risk of energy loss caused by delays in adaptation, which is particularly crucial in environments with frequently changing tidal velocities.

These results confirm that the A-ORB MPPT algorithm outperforms the BI-PSO, SS-PO, and SS-InC MPPT algorithms in both convergence speed and power output. The A-ORB MPPT algorithm's ability to rapidly and efficiently track the MPP makes it a promising approach for optimizing tidal energy extraction. This capability maximizes energy capture and ensures that the system quickly responds to changing conditions, thereby maintaining optimal performance and minimizing potential energy losses.

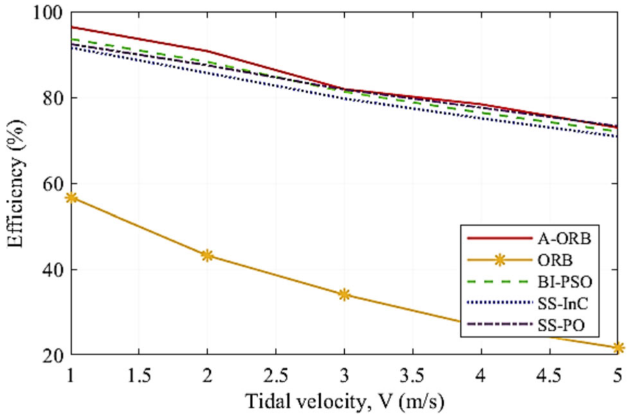

Fig. 8 Efficiency of MPPT algorithms across varying tidal velocities

2.7 Tracking Accuracy

Higher tracking accuracy directly enhances MPPT system efficiency. The algorithm's tracking ability, measured by output power accuracy, ensures operation at the MPP, reducing power losses and maximizing energy extraction. Output power efficiency is evaluated by comparing the theoretical maximum power with the actual output. Precise tracking minimizes steady-state oscillations and enables rapid adaptation to change conditions, improving overall system efficiency and energy yield. This capability is essential for optimizing the benefits of renewable energy sources.

Table 5 presents a performance comparison of four MPPT algorithms (SS-PO, SS-InC, BI-PSO, and A-ORB) across tidal velocities ranging from 2.25 to 3.25 m/s. The key metrics analyzed include extracted output power (in watts) and efficiency (in percentage). The A-ORB MPPT algorithm consistently achieves the highest efficiency across all tidal velocities, with a peak efficiency of 96.39%. This higher efficiency signifies better utilization of available energy, establishing the A-ORB MPPT as a superior choice for maximizing energy output in tidal energy systems.

Figure 8 presents a graphical representation of the efficiency percentages across tidal velocities for each MPPT algorithm. The graph highlights the consistent superiority of the A-ORB MPPT algorithm, which achieves the highest efficiency across all tested velocities. In contrast, the ORB MPPT algorithm exhibits a significant decline in efficiency at higher tidal velocities, making it less reliable for stable energy production.

At higher tidal velocities, the A-ORB MPPT algorithm consistently matches or exceeds the theoretical maximum power available. This consistent performance across varying tidal conditions ensures reliable energy production, which is critical for the stability and predictability of tidal energy systems. In contrast, the SS-InC MPPT algorithm consistently exhibits the lowest efficiency and output power across all tidal velocities, making it the least effective among the tested algorithms. While the BI-PSO and SS-PO MPPT algorithms outperform SS-InC, they still fall short of the A-ORB MPPT in both efficiency and output power. This comparison underscores the importance of selecting an optimal MPPT algorithm to maximize energy extraction. The superior performance of the A-ORB MPPT can contribute to more efficient and reliable tidal energy systems.

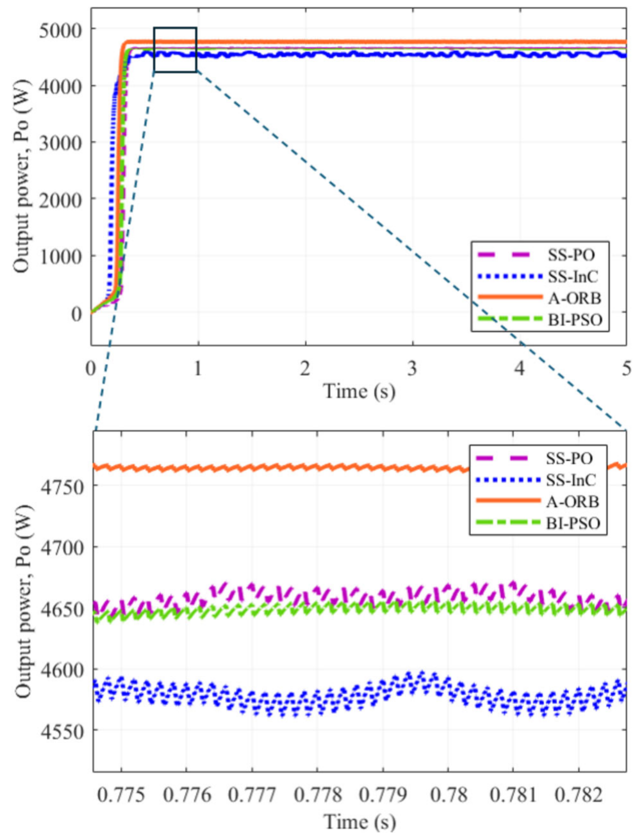

Fig. 9 Output power oscillations at 2.5 m/s tidal velocity for different MPPT methods with reduced fluctuations in the A-ORB algorithm

2.8 MPPT Oscillations

MPPT oscillations refer to fluctuations in output power around the MPP. These oscillations arise because the MPPT algorithm continuously adjusts the system's operating point to locate and maintain operation at the MPP. As illustrated in Fig. 9, all four methods exhibit increased power oscillations around the MPP as tidal velocity increases.

Table 6 presents the oscillation values at various tidal velocities for different MPPT methods. The A-ORB MPPT method consistently exhibits significantly lower oscillations than the SS-PO, SS-InC, and BI-PSO MPPT algorithms. For instance, at a tidal velocity of 2.5 m/s, the A-ORB method has an oscillation value of 3.1 W, while SS-PO, SS-InC, and BI-PSO MPPT exhibit 13.6, 16.2, and 8.8 W, respectively.

Table 5 The extracted output power and efficiency

Tidal velocity (m/s)	Output power, Po (W)						Efficiency (%)				
	Maximum available power	SS-PO	SS-InC	BI-PSO	ORB	A-ORB	SS-PO	SS-InC	BI-PSO	ORB	A-ORB
2.25	3883	3587	3555	3634	2202	3743	92.38	91.55	93.59	56.71	96.39
2.5	5326	4658	4561	4699	2298	4833	87.46	85.64	88.23	43.15	90.74
2.75	7089	5797	5648	5761	2413	5804	81.77	79.67	81.27	34.04	81.87
3	9203	7140	6909	7029	2452	7211	77.58	75.07	76.38	26.64	78.35
3.25	11,701	8570	8288	8427	2535	8532	73.24	70.83	72.02	21.66	72.92

Table 6 The oscillation of the output power at different tidal velocities

Tidal velocity (m/s)	Oscillation (W)			
	SS-PO	SS-InC	BI-PSO	A-ORB
2.25	10.9	16.9	7.1	2.9
2.5	13.6	16.2	8.8	3.1
2.75	17.8	21.1	9.4	2.2
3	21.4	24.5	12.2	4.9
3.25	25.7	31.1	14.5	6.4
Average	17.88	21.96	10.4	3.9

These lower oscillation values with the A-ORB method indicate reduced fluctuations around the MPP. Consequently, power loss due to these oscillations is minimized, leading to a more stable and efficient system, as described in [38]. Therefore, the A-ORB method's ability to reduce oscillations contributes to minimizing power loss associated with fluctuations, thereby increasing overall system efficiency.

The superior stability of the A-ORB MPPT algorithm enhances both system reliability and efficiency, particularly in dynamic tidal conditions where fluctuations can significantly impact energy capture. By minimizing power fluctuations, the A-ORB MPPT algorithm reduces the risk of energy losses associated with oscillatory behavior. The average oscillation value further demonstrates its effectiveness. With an average oscillation of only 3.9 W, the A-ORB MPPT outperforms SS-PO (17.88 W), SS-InC (21.96 W), and BI-PSO (10.4 W) by a substantial margin. In summary, the results confirm that the A-ORB MPPT algorithm is superior in minimizing output power oscillations, thereby improving the overall efficiency and reliability of tidal energy systems. This makes it a promising approach for optimizing energy capture in dynamic and fluctuating tidal conditions.

2.9 Robustness Test

The dynamic response of the SS-PO, SS-InC, A-ORB, and BI-PSO MPPT algorithms under sudden tidal velocity changes highlights differences in performance. Figure 10 illustrates the velocity variations, while Fig. 11 depicts each algorithm's adaptation. During steady-state conditions before and after the velocity change, all algorithms maintain stable power output; however, the A-ORB MPPT algorithm achieves the highest steady-state power, indicating superior MPP tracking efficiency. BI-PSO follows closely, while SS-PO and SS-InC produce lower power outputs, reflecting reduced tracking accuracy. In response to the sudden velocity change at 2 s, the A-ORB MPPT algorithm demonstrates the fastest transient recovery, stabilizing within 26 ms, followed by BI-PSO at 43 ms. In comparison, SS-PO and SS-InC take significantly longer to stabilize, at 64 and 85 ms, respectively.

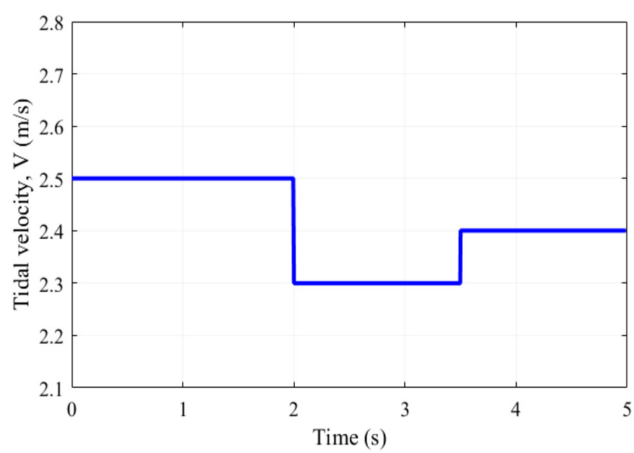

Fig. 10 The sudden changes in tidal velocity

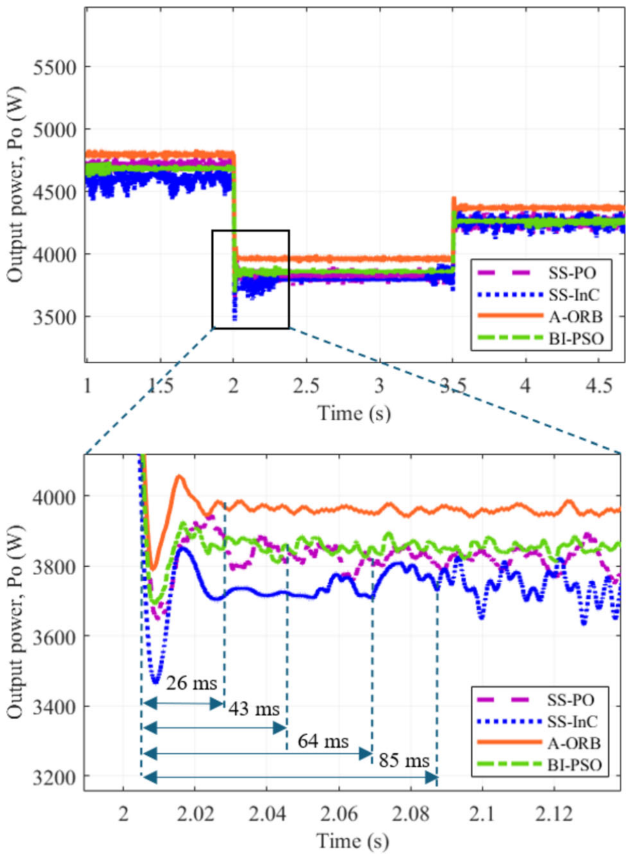

Fig. 11 Dynamic response of MPPT algorithms to sudden tidal velocity changes

Furthermore, the A-ORB MPPT algorithm exhibits minimal overshoot and the smoothest recovery with negligible oscillations, whereas SS-InC experiences the largest undershoot and persistent fluctuations, revealing its lower adaptability to dynamic conditions.

These results underscore the A-ORB MPPT algorithm's superior robustness, making it the most suitable choice for real-world tidal energy applications where velocity changes are frequent and unpredictable. The BI-PSO algorithm also performs well, balancing response speed and stability, whereas SS-PO and SS-InC exhibit limited robustness, with slower responses and greater susceptibility to transient disturbances. Overall, this analysis highlights the importance of dynamic performance in MPPT design, as the ability to quickly stabilize power output with minimal oscillations ensures reliable and efficient operation of tidal energy systems. The A-ORB MPPT algorithm establishes a benchmark for future advancements in adaptive MPPT strategies.

One of the key challenges in evaluating MPPT techniques for TECS is the limited availability of real-world experimental data. However, numerous studies have successfully demonstrated the effectiveness of simulation-based MPPT validation, particularly in the fields of wind and PV energy systems. Table 7 presents a comparison of existing MPPT techniques validated in previous research, including conventional, intelligent, and hybrid approaches. The results indicate that while methods such as Improved P&O [30] and modified P&O [28] achieve high efficiency, they suffer from increased oscillations and complexity, particularly when applied to wind and PV systems. Similarly, hybrid techniques such as hybrid InC [22] and hybrid ORB [29] have been validated for wind and tidal energy conversion systems, highlighting improvements in tracking speed and efficiency.

In the present work, the A-ORB method is evaluated under a range of simulated tidal conditions, incorporating parameter variations and dynamic flow changes. The simulated environment ensures consistency in assessing the performance of different MPPT strategies before practical implementation. Future work will explore experimental validation to further confirm the feasibility of A-ORB in real-world TECS applications.

3 Conclusion

This study evaluates the performance of the A-ORB MPPT algorithm in comparison with conventional SS-PO, SS-InC, and BI-PSO MPPT algorithms for a tidal energy conversion system. The findings indicate that the A-ORB MPPT algorithm achieves a faster convergence rate of 0.32 s and a higher efficiency of 96.39% at a 2.5 m/s tidal velocity, outperforming the SS-PO method (87.46%), SS-InC (85.64%), and BI-PSO MPPT algorithm (93.59%). Additionally, the A-ORB algorithm demonstrates superior performance at lower tidal velocities, ensuring more stable and efficient energy capture. The key scientific contributions of this study include the development of a hybrid MPPT strategy that integrates the ORB method with HCS, improving adaptability to tidal fluctuations. Furthermore, the introduction of an adaptive gain factor adjustment dynamically tunes K based on power variations (ΔP), effectively reducing power oscillations and enhancing MPP stability. The results confirm that the A-ORB algorithm achieves superior tracking efficiency compared to conventional and bio-inspired MPPT methods, particularly under dynamic tidal conditions. These advancements contribute to improving the robustness and adaptability of MPPT techniques for tidal energy conversion, addressing key limitations such as oscillations in P&O and slow convergence in InC. However, this study is currently limited to simulation-based validation, and no hardware or hardware-in-the-loop (HIL) testing has been conducted. Future work focuses on implementing the A-ORB MPPT algorithm in real-world applications to verify its practical effectiveness. Additional enhancements include

Table 7 Comparison of the proposed MPPT strategy with previous research work

Parameters	MPPT strategies				
	Improved P&O	Modified P&O	Hybrid InC (PSO + InC)	Hybrid ORB (FLC + ORB)	A-ORB
Reference	[27]	[28]	[22]	[29]	Proposed method
Application	PV	Wind	Wind	Tidal	Tidal
Algorithm type	Conventional	Conventional	Intelligent	Intelligent	Conventional
Convergence speed	High	High	High	High	High
Oscillation	High	High	Low	Low	Low
Efficiency	High	Good	Good	High	High
Tracking time (s)	0.003	0.02	Not mentioned	Not mentioned	0.026
Complexity	Low	Low	Medium	Medium	Low

optimizing the algorithm for highly variable tidal flows, integrating it into larger tidal energy systems, and incorporating machine learning techniques to improve prediction accuracy and adaptability. These improvements aim to ensure greater reliability and efficiency in tidal energy conversion, supporting the advancement of sustainable ocean energy technologies.

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Data Availability The data supporting the findings of this study can be obtained from the corresponding author upon a reasonable request.

Declarations

Conflict of interest No potential conflict of interest was reported by the author(s). The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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