

Data-driven predictive modeling and optimization of biomimetic wave energy converters: A review with focus on Malaysian marine environments

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ABSTRACT

Ocean waves are a reliable and high energy density renewable resource in coastal regions; however, their utilization is still very limited by constraints of wave energy converters (WECs) and variable wave climate. Biomimetic wave energy converters (BWECs), influenced by the adaptive architectures of marine organisms, possess the capacity to address structural and efficiency challenges. Nonetheless, their design and optimization require highly precise predictions of wave conditions and device performance, which conventional numerical and statistical methods are incapable of achieving. Artificial intelligence (AI) and machine learning (ML) methods have shown great promise for overcoming these constraints, with studies investigating ensemble models, deep learning structures, time-series architectures, and reinforcement learning for forecasting and converter control. However, data-driven predictive modeling in relation to BWEC design optimization for the low-energy monsoon-affected Malaysian coastline is not extensively studied. This review systematically analyzes 231 articles published in Scopus, Web of Science, and IEEE Xplore (2010–2026) on predictive models for wave resource estimation, power production, hydrodynamics, and adaptive control. Input features, benchmark datasets, and current research gaps are also analyzed. Ensemble stacking models achieve $R^2 \geq 0.89$ – 0.99 on benchmark WEC farm and buoy datasets; hybrid LSTM architectures achieve $R^2 > 0.99$ under single-site stationary conditions; and RL-MPC improves simulated power output by up to 185% over passive baselines — though generalizability to Malaysia's monsoon-modulated climate remains unvalidated. Critical gaps persist in Malaysian model validation, Transformer architectures, and physics-informed neural networks. This review integrates BWEC design, AI/ML predictive modeling, and Malaysian coastal constraints as a unified framework.

1. Introduction

Global energy demand rose rapidly in the past decade as a result of accelerating urbanization, industrialization and population growth, but as the effects of climate change grew due to the continued reliance on fossil fuels, global momentum shifted increasingly towards sustainable and low-carbon energy systems [1]. Among the renewable energies, ocean energy has proven to be a good prospect, yet an under exploited source of energy, and has some inherent advantages in comparison with established renewable technologies such as solar and wind energy [2,3]. In particular, ocean wave energy has been the subject of great interest because of its high energy density and fairly predictable time variation [4]. Wave energy has an estimated power density of

approximately (2 – 3 kW m^{-2}), which is more than one order of magnitude higher than wind energy (0.4 – 0.6 kW m^{-2}) and nearly two orders of magnitude higher than solar energy (0.1 – 0.2 kW m^{-2}) [4]. The estimated global wave power resource is approximately 3.7 TW , with over 2 TW considered technically exploitable [5]. This plentiful but underused energy source could be a good way to make sustainable electricity and make sure that there is a long-term supply of energy in places with lengthy coasts [6–8].

WECs are specially designed mechanical systems that capture the kinetic and potential energy of ocean waves and convert it into electrical energy [9]. Although WEC technology has been developed over many years, a wide-scale implementation of its arrays is still scarce,

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List of Abbreviations

Abbreviation	Full term
AEP	Annual Energy Production
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMA	AutoRegressive Moving Average
BEM	Boundary Element Method
BiGRU	Bidirectional Gated Recurrent Unit
BiLSTM	Bidirectional Long Short-Term Memory
BWEC	Biomimetic Wave Energy Converter
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
CWR	Capture Width Ratio
DDPG	Deep Deterministic Policy Gradient
DNN	Deep Neural Network
DQN	Deep Q-Network
ECMWF	European Centre for Medium-Range Weather Forecasts
ERA5	ECMWF Reanalysis v5
FSI	Fluid-Structure Interaction
GAN	Generative Adversarial Network
GBM	Gradient Boosting Machine
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
H_s	Significant Wave Height
kNN	k-Nearest Neighbors
LightGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
MARL	Multi-Agent Reinforcement Learning
ML	Machine Learning
MLP	Multi-Layer Perceptron
MPC	Model Predictive Control
NDBC	National Data Buoy Center
NOAA	National Oceanic and Atmospheric Administration
OWC	Oscillating Water Column
OWSC	Oscillating Wave Surge Converter
PINN	Physics-Informed Neural Network
PPO	Proximal Policy Optimization
PTO	Power Take-Off
PTFE	Polytetrafluoroethylene
PVDF	Polyvinylidene Fluoride
RANS	Reynolds-Averaged Navier–Stokes
RF	Random Forest
RL	Reinforcement Learning
SAC	Soft Actor–Critic
SCS	South China Sea
SVR	Support Vector Regression
SWAN	Simulating WAVes Nearshore
TAP	Total Absorbed Power
T_p	Peak Wave Period
VOF	Volume of Fluid
WEC	Wave Energy Converter
XGBoost	Extreme Gradient Boosting

mainly because of large initial investment, inefficiency, and considerable survivability problem in severe offshore marine conditions [10]. Despite the fact that wave energy resources are available along the more than 70% of the world's coastlines, wave power still accounts for a small fraction in the world renewable energy mix, primarily because that over 90% of potential sites for wave energy are subject to high temporal variability induced by meteorological and seasonal climate patterns [10,11]. These challenges highlight the need to develop efficient, reliable, and cost-effective WEC technologies capable of operating under highly variable ocean conditions [12].

In response to these challenges, biomimetic engineering has emerged as a promising strategy for improving WEC performance and survivability by drawing inspiration from marine organisms that have naturally

evolved to operate efficiently in dynamic ocean environments. Marine creatures including rays, fish, and jellyfish demonstrate highly optimized hydrodynamic propulsion with undulating fins, oscillating foils, and pulsating jet propulsion mechanisms, respectively, which offer promising design inspirations to WEC configurations with improved hydrodynamic performance, structural flexibility, and energy extraction potential [12]. A BWEC is defined as a bio-inspired device that utilizes biological concepts concerning shape, motion, material properties, or control strategies to enhance energy extraction efficiency and system resilience [13].

Malaysia offers a significant case study for the advancement of BWEC technology. With a coastline extending approximately 4675 km, the country possesses considerable nearshore wave energy resources that are considered among the most strategically promising renewable energy options for coastal and island communities [14]. The offshore wave power density in the South China Sea varies from approximately 50 to 500 kW m⁻¹, whereas the nearshore power densities along the eastern coast of Peninsular Malaysia and the Malacca Strait range from 10 to 40 kW m⁻¹. Coastal areas such as Perak, Terengganu, Sarawak, and Sabah have been identified as principal sites for energy harvesting [15]. The numerous small islands throughout the country rely extensively on imported fossil fuels for electricity generation, with elevated fuel transportation costs and geographic isolation severely limiting economic development. Consequently, the deployment of WEC presents a feasible route to achieve localized energy independence and sustainable electrification [16].

Despite the mean significant wave heights in Malaysian waters being relatively modest, between approximately 1.0 and 1.5 m, nearshore environments are appealing for WEC deployment due to their feasible installation depths and lower infrastructure costs compared to offshore systems [17,18]. Malaysian wave resources indicate low mean power density and considerable seasonal variability, with significant wave heights between 0.5 and 2.0 m and peak periods ranging from 4 to 8 s, further influenced by monsoonal and inter-annual climatic patterns [17,18]. The low-energy but highly variable conditions impose considerable design requirements on WEC technologies, which are typically optimized for the high-energy, long-period swells of the North Atlantic and North Pacific, rendering them fundamentally inappropriate for Malaysian coastal environments [19]. Recent research has focused on nearshore oscillating water column (OWC) devices, point absorbers, and hybrid systems, where biomimetic concepts may improve energy capture efficiency and device durability in the irregular, low-amplitude wave conditions typical of Malaysian coasts [20]. Biomimetic optimization techniques are essential for improving the performance and commercial feasibility of wave energy in this region [19].

Accurate predictive modeling of WEC performance is critical for maximizing energy capture, maintaining grid stability, and demonstrating the financial viability of wave energy projects in regions of low and highly variable wave climate such as Malaysia [21]. Traditional numerical and statistical prediction methods face fundamental limitations in capturing the nonlinear and time-varying dynamics of ocean waves influenced by monsoonal systems and inter-annual climate oscillations [22]. Consequently, artificial intelligence and machine learning techniques — including convolutional neural networks (CNNs), long short-term memory (LSTM) networks, ensemble learning methods, and Transformer-based architectures — have demonstrated strong capability in modeling the complex spatial and temporal dynamics of ocean wave systems [23,24]. The integration of AI-based predictive modeling with adaptive BWEC design therefore provides new opportunities to improve energy capture efficiency, device survivability, and operational planning under variable sea states, supporting the sustainable electrification of coastal and island communities in Malaysia [25,26].

Notwithstanding the growing body of research on BWEC design and machine-learning-based wave energy forecasting, the literature still lacks a unified review that explicitly integrates data-driven predictive modeling as an optimization framework specifically for BWECs within a

defined low-energy tropical deployment context such as Malaysia [19, 27]. Existing reviews either address WEC hydrodynamics, geometry, and device optimization without systematically treating modern data-driven prediction and control methods, or they survey machine learning and deep learning for wave and wind energy forecasting and generic WEC optimization without distinguishing biomimetic devices as a distinct design category [12,27–29]. Moreover, the modeling and forecasting difficulties unique to low-amplitude, highly seasonal, monsoon-influenced wave regimes in Malaysian and wider Southeast Asian waters have not been rigorously investigated [30]. Regional resource studies indicate that Malaysian seas exhibit low significant wave heights significantly influenced by monsoonal forces [31]—conditions that are fundamentally distinct from the high-energy North Atlantic environments that serve as the basis for most WEC and ML benchmarks [32]. This gap is notably important considering Malaysia's strategic necessity for localized, island-scale renewable energy solutions, as recent assessments of ocean renewable energy emphasize the modest yet persistent wave resource and the need for customized technologies, while failing to link these limitations to BWEC optimization or sophisticated data-driven control frameworks [31,33]. This review employs Malaysian coastal constraints as a cohesive framework, assessing the hydrodynamic suitability of various BWECs, the validity of modeling assumptions, and the efficacy of AI/ML architectures in data-scarce, monsoon-influenced conditions. Each section systematically inquires not only into global knowledge but also into its genuine applicability to Malaysia's low-energy, monsoon-modulated nearshore environment.

To address this gap, the present review is focused on: (1) reviewing and categorizing BWEC designs based on biological inspiration, working principle, architecture, and applicability to Malaysian coastal conditions; (2) characterizing the wave energy resource of Malaysian seas across offshore, strait, and nearshore regions and assessing the implications for BWEC design and siting; (3) reviewing modeling approaches for BWECs, including analytical, physics-based, CFD, statistical, and empirical methods; (4) providing a comprehensive review of AI and ML-based predictive modeling frameworks — encompassing traditional ensemble models, feedforward and spatial deep learning, time-series architectures, reinforcement learning, and physics-informed methods — for WEC performance prediction, wave forecasting, and control optimization; (5) identifying key input features, benchmark datasets, and performance metrics from the reviewed literature; and (6) summarizing existing research gaps and proposing future research directions for data-driven optimization of BWECs in Malaysia and comparable low-energy tropical coastal environments (see Fig. 1).

A bibliometric analysis was conducted to assess the distribution of studies in BWEC and AI/ML-based wave energy forecasting, employing three principal academic databases — Scopus, Web of Science, and IEEE Xplore — covering the period from 2010 to 2026. Ten keyword string combinations were employed, encompassing machine learning, deep learning, LSTM, reinforcement learning, physics-informed neural networks, BWEC design, and Malaysia-specific wave energy research. Fig. 2 demonstrates that the search produced a total of 1392 documents, with Scopus accounting for the majority ($n = 875$, 62.9%), followed by Web of Science ($n = 320$, 23.0%) and IEEE Xplore ($n = 197$, 14.2%). The search term *wave energy* AND *LSTM* produced the highest total results ($n = 398$), demonstrating the dominance of recurrent deep learning frameworks in current wave energy research, followed by *biomimetic* AND *wave energy* ($n = 238$) and *WEC* AND *machine learning* ($n = 232$). The search term *Malaysia* AND *wave energy* produced a significant number of results from IEEE Xplore ($n = 97$ out of 215 total), indicating that research on Malaysian wave energy is mostly published in conference proceedings rather than in indexed journals. At the other extreme, *wave energy* AND *PINN* returned only 29 results, and *WEC* AND *transformer* AND *forecasting* retrieved zero results across all three databases. This absence reflects not a lack of Transformer adoption in energy forecasting broadly, but rather

the absence of a unified framework explicitly coupling Transformer-based prediction with WEC design and optimization—a gap the present review is positioned to address. Following duplicate removal and the application of title, abstract, and full-text screening criteria, 231 papers were retained for inclusion in this review.

This review is organized to present a comprehensive overview of BWECs in Malaysian waters. Sections 2 and 3 delineate the fundamentals of wave energy and traditional WEC technology. Sections 4 and 5 analyze BWEC design, biological inspiration, and site-specific resource attributes. Sections 6 and 7 examine modeling methodologies and essential input features, whereas Section 8 evaluates AI and ML frameworks for forecasting, power prediction, and adaptive control. Section 9 ultimately encapsulates findings, delineates research deficiencies, and proposes future trajectories for data-driven BWEC optimization.

2. Overview of wave energy

Wind, solar, hydropower, and ocean waves are all major renewable resources that are universally accepted as clean, sustainable, and relatively mature possibilities for generating energy with no hazardous emissions [34–36]. When compared to wind (about $0.4\text{--}0.6\text{ kW m}^{-2}$) and solar (roughly $0.1\text{--}0.2\text{ kW m}^{-2}$), wave energy stands out due to its greater energy density of about ($2\text{--}3\text{ kW m}^{-2}$) [36,37]. With a global theoretical capacity of roughly 29,500 TWh annually [38], wave energy also demonstrates good predictability and comparatively little environmental effect. According to life cycle assessment studies, modern WECs can achieve CO_2 emissions as low as $21\text{ g CO}_2\text{-eq/kWh}$ [39], which is significantly lower than those of fossil-fuel-based power generation systems. However, a number of technical and financial issues pertaining to cost, structural durability, and wave variability still have an impact on large-scale deployment [29].

3. Wave energy converters (WECs)

WEC is an apparatus that captures mechanical energy from the waves of the ocean and transforms it to electricity [40]. WECs cause interaction between the component and the surrounding water by responding to wave-induced motions such as heave, surge, and pitch. A power take-off system turns mechanical motion into electrical energy using hydraulic, pneumatic, or direct-drive mechanisms. Depending on the deployment design, the generated electricity is conditioned before being delivered to shore or integrated into the local energy system [41].

As shown in Fig. 3, WECs are classified by working principle into five categories: oscillating water columns (OWCs), oscillating body systems, overtopping devices, pressure differential devices, and bulge wave devices [42]. Oscillating body systems are further divided into point absorbers, oscillating wave surge converters (OWSCs), and attenuators, each differing in geometry and orientation. As indicated in the lower panel of Fig. 3, biomimetic design inspirations are not a separate working-principle class but are applied across these categories [12]; their detailed classification by biological feature is addressed in Table 1.

3.1. Device-based classification

WECs can be conceptually grouped according to their functional architecture and interactions with ocean waves. Point absorbers, oscillating water columns (OWCs), oscillating wave surge converters (OWSCs), terminators, and overtopping devices represent the principal categories, each suited to distinct wave conditions and installation scenarios [41]. Malaysian nearshore waters — characterized by significant wave heights of $0.5\text{--}2.0\text{ m}$, peak periods of $4\text{--}8\text{ s}$, and strong monsoon-driven seasonality — impose specific compatibility constraints on each device type, which are noted below.

1. Point Absorbers: Point absorbers are compact devices that harness wave energy from several directions through vertical or horizontal oscillations [43,44]. These devices are frequently arranged in arrays

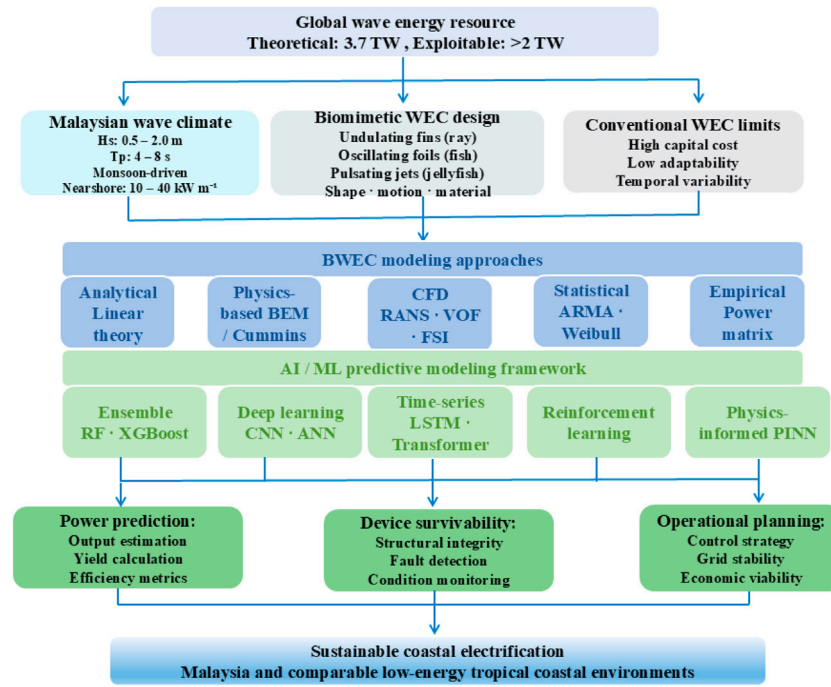


Fig. 1. Conceptual review framework incorporating biomimetic wave energy converter design, modeling methodologies, and AI/ML-based predictive techniques for sustainable coastal electrification in Malaysia.

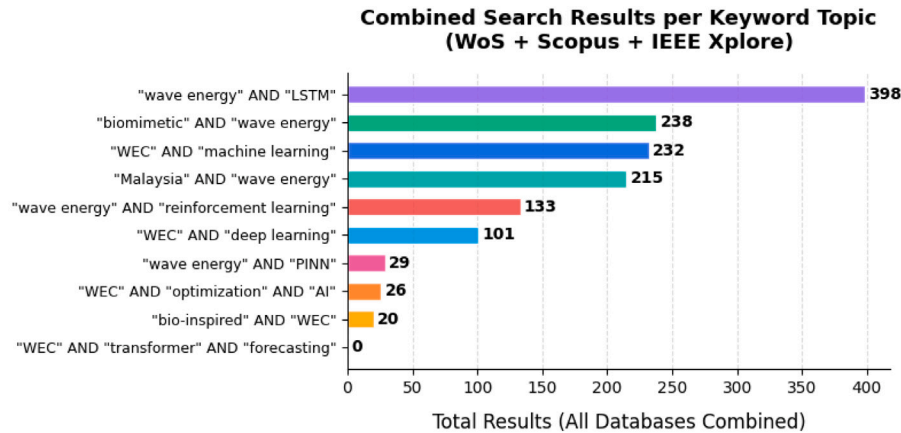


Fig. 2. Bibliometric search results by keyword combination across Scopus, Web of Science, and IEEE Xplore (2010–2026).

to enhance hydrodynamic efficiency via unit interactions. Their fundamental design and adaptability render them suitable for many wave situations [45]. They are effective in moderate wave energy conditions and necessitate meticulous engineering. In Malaysian nearshore deployments at depths of 10–20 m, point absorbers with resonance diameters of 2–5 m are geometrically suitable for the local wave climate; however, active resonance tuning is essential to sustain performance amid significant seasonal energy fluctuations between the northeast and southwest monsoon periods, thereby ensuring durability and energy capture [46].

2. Oscillating Water Columns (OWCs): OWCs use oscillating water levels in a partially submerged chamber to capture wave energy and move air through a turbine to produce electricity. In OWCs, air is compressed and decompressed by wave-induced oscillation of the water column, which powers a self-rectifying turbine connected to a generator. OWC devices are not restricted to nearshore fixed installations; floating offshore OWC concepts such as the Spar-OWC and OE Buoy are equally well established, and fixed nearshore configurations represent one of several deployment modes. The effectiveness and

deployment possibilities have been greatly enhanced by recent multi-chamber and geometric modifications [47,48]. For Malaysian coastal conditions, fixed nearshore OWCs are the more practical near-term configuration, and impulse turbines are preferred over Wells turbines owing to their superior efficiency across the short and irregular wave periods characteristic of the east coast of Peninsular Malaysia.

3. Oscillating Wave Surge Converters (OWSCs): OWSCs operate by harnessing the surge motion of waves impacting a moveable floating flap in shallow waters, around 10 to 20 m deep. Hydraulic systems convert kinetic motion into electrical energy. Current research emphasizes the improvement of flap hydrodynamics and the hybrid integration with other maritime energy infrastructures; these devices operate effectively in high-energy coastal regions [49,50]. Of all conventional WEC types, OWSCs exhibit the highest hydrodynamic compatibility with Malaysian nearshore conditions: their surge-dominated response corresponds seamlessly with the directional wave characteristics of the east coast, their operational depth of 10–20 meters aligns with the typical Malaysian nearshore bathymetry, and their broad frequency

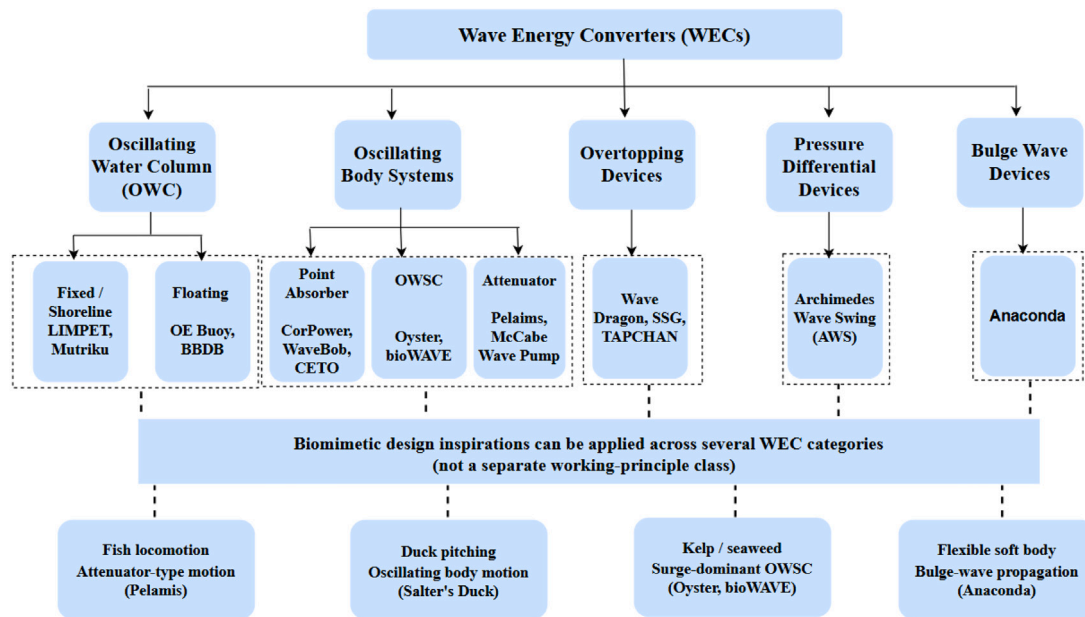


Fig. 3. Classification of wave energy converters by working principle [42], with biomimetic design inspirations mapped across device categories [12].

response accommodates the variability in wave conditions driven by the monsoon.

4. Terminators: Terminators are linear, offshore wave energy converters that optimize energy capture across an extensive surface area by positioning themselves perpendicular to wave fronts. Despite higher construction and maintenance costs, their robust design facilitates effective operation under high-energy marine conditions. Terminators are suitable for demanding offshore conditions since permanent magnet linear generators provide direct energy conversion with reduced mechanical losses [51,52]. Terminators are designed for high-energy offshore waves with energy periods beyond 8 s, making them unsuitable for deployment in Malaysian nearshore environments, where wave times are significantly shorter and energy densities markedly lower.

5. Overtopping Devices: Overtopping WECs capture energy by directing incoming waves over a ramp structure into a raised reservoir, from which water flows back to sea through low-head turbines. Wave Dragon is the principal large-scale example [53]. These devices are designed for offshore, high-energy, long-period swells and are not suitable for the short-period, low-energy conditions characteristic of Malaysian nearshore waters and are viable in the Malaysian context only within the high-energy South China Sea offshore zone.

3.2. Energy conversion and power take-off mechanisms

The PTO mechanism, which transforms wave-induced mechanical motion into electrical energy, regulates energy conversion in WECs. The design of the PTO system significantly influences total conversion efficiency, operating lifespan, and maintenance needs, rendering it a crucial factor for wave energy implementation in diverse maritime environments like Malaysian coastal waters [54]. Hydraulic PTOs are commonly employed in high-load scenarios due to their remarkable conversion efficiency; nonetheless, they present challenges related to maintenance complexity and leakage problems [54]. Hydraulic systems achieve rated efficiencies of 70%–85% under optimal conditions; however, part-load efficiency significantly decreases at sub-design wave heights, which poses a critical limitation for Malaysian nearshore waters where H_s frequently falls below 1.0 m during inter-monsoon periods [54,55]. Under stable wave circumstances, mechanical PTOs offer enhanced directness and reliability in functionality [55]. Direct-drive linear generators (DDLGs), functioning as permanent magnet linear generators (PMLGs), directly convert oscillatory motion into

electricity without hydraulic intermediaries, attaining rated efficiencies of 85%–95% at design speed [56]; however, performance diminishes at off-resonance frequencies, requiring active resonance tuning for Malaysian waters where $T_p = 4\text{--}8$ s is shorter than the natural periods of most devices [56]. Air turbines function as the power take-off mechanism for oscillating water column (OWC) devices: Wells turbines are self-rectifying but attain only 60%–70% efficiency, whereas impulse turbines provide 75%–85% efficiency over a wider operational range; for Malaysian OWC installations characterized by short, irregular wave periods, impulse turbines with variable guide vanes are favored [46]. Although triboelectric nanogenerators are suitable for low-power applications [57], their use in severe maritime conditions necessitates rigorous material selection criteria. TENGs function through contact-separation or sliding-mode electrostatic induction between two triboelectric layers possessing contrasting charge affinities, with power output significantly reliant on surface charge density and the tribological compatibility of the chosen materials [58]. Marine-grade TENG materials must achieve a compromise between superior triboelectric performance and resilience to seawater corrosion, bio-fouling, and mechanical fatigue under cyclic wave loading [59]. Fluoropolymers, including polytetrafluoroethylene (PTFE) and fluorinated ethylene propylene (FEP), have been the most popular choice for the electronegative layer, owing to their chemical inertness, hydrophobic property, and constant charge retention in saltwater [60]. The electropositive layers mostly consist of nylon or polyamide composites, which require encapsulation or coating with a hydrophobic layer to maintain stable performance in aqueous environments [59,60]. Innovative techniques incorporate liquid-metal electrodes and silicone elastomers in BWEC designs to achieve triboelectric characteristics and structural flexibility; nevertheless, data about long-term ocean endurance is few [61]. Environmental constraints, including UV exposure, seasonal temperature variations, and the accumulation of abrasive particles in nearshore Malaysian waters, limit feasible material options outside laboratory environments [57,58]. Emerging technologies like dielectric elastomer generators provide lightweight and economical alternatives [1,62]. Linear energy producers continue to be the preferred option for large-scale grid-integrated WECs [56].

Control strategies critically determine captured power fraction. Passive resistive damping establishes the performance baseline with a capture efficiency of 15%–35% [63]. Reactive control optimizes power acquisition by the integration of resistive and spring-like PTO forces;

yet, it necessitates bidirectional power flow, hence augmenting structural loads [63]. Latching control, especially applicable to Malaysian nearshore settings characterized by dominant wave periods shorter than the device's natural periods, phase-shifts the device's reaction to near-resonance without enabling bidirectional power flow [63,64]. The MPC enhances PTO force through short-term wave projections, resulting in a 20%–60% increase in power compared to passive baselines [63, 64], hence justifying the AI/ML forecasting approach discussed in the subsequent section.

3.3. Limitations of conventional WEC technologies

The efficiency and broad use of traditional WECs are constrained by a number of significant issues. Common WEC designs, such as point absorbers, oscillating water columns, and overtopping devices, often require considerable mechanical complexity, are expensive to maintain, and can be susceptible to adverse marine environmental conditions [65, 66]. High sensitivity of the efficiency to unpredictable wave patterns leads to a highly irregular power output. In addition, normal wave fatigue may result in structural damage to traditional WECs, limiting their operating life and increasing their maintenance cost [67]. The potential for noise pollution and marine habitat disruption means that environmental effects are limiting factors also affecting large-scale implementation [67]. Many of these limitations are overcome by BWECS, which are based on movement and adaptation mechanisms of marine animals [41]. By mimicking certain nature forces, such as the variable undulation of fish or the repetitive movement of fins, BWECS can better adapt to and harvest energy from a wider range of wave states [12]. They are a promising candidate for reliable and sustainable wave energy harvesting with enhanced environmental friendliness, reduced mechanical complexity, and heightened structural robustness.

4. Biomimetic Wave Energy Converters (BWECS)

Biomimetics is the application of biological rules, templates, and mechanisms in the natural world to solve challenging engineering problems [68,69]. Inspired by the swimming mechanisms, flexibility, and survival strategies of marine creatures such as jellyfish, fish, kelp, and mollusks, BWECS are being developed in the wave energy engineering area [13]. Therefore, BWECS are characterized by compliant motion and adaptive response, which enable higher broadband harvesting energy and higher survivability in irregular and severe sea states compared with classical rigid WECs designed for narrow wave spectra [12,70]. The marine life can be found in very active wave environments, and they have the ability to keep stable oscillatory motion with constant hydrodynamic force [71]. This biological robustness inspires BWECS designs that seek to bestow together hydrodynamic efficiency, structural compliance, and environmental compatibility [71]. Therefore, BWECS are taking more and more attention as a solution to the limitations of traditional WECs, such as structural breakdown, narrow band tuning, and environmental impact [70].

4.1. Biological feature-based classification of BWECS

Biomimetic wave energy converters (BWECS) are characterized by their replication of specific biological features — such as shape, motion, structure, or operating principles — drawn from marine organisms. In the literature, the boundary between conventional and biomimetic WECs is not sharply defined. Many early devices were developed before the term “biomimetic” became common in wave energy research. Devices such as Pelamis (an articulated attenuator) and Salter's Duck (a pitching terminator) are historically regarded as foundational conventional concepts. However, Zhang and Aggidis [12] analyze these and other WECs through a biomimetic lens, identifying “nature rules” based on kinematic and morphological analogies (e.g., sea-snake-like locomotion in Pelamis and duck-like pitching in Salter's Duck).

Table 1

Classification of BWECS by biological mimic strategy.

Category	Mimicked feature	Example BWECS
Single-feature	Function	bioWAVE [76]
	Motion	Jellyfish, Penguin [77]
	Structure	Centipod [78]
	Shape	Wave Dragon, Salter Duck [78]
	Principle	Sea Heart [12]
Multi-feature	Behavior	Oyster, WaveStar [78]
	Shape + Motion	Pelamis [79]
	Shape + Principle	Anaconda [77,79]

This review follows the classification framework of Zhang and Aggidis [12] for highlighting biomimetic inspirations, while also grounding the discussion in more widely accepted WEC taxonomies based on operating principle (oscillating water column, oscillating bodies, overtopping, and pressure differential) and orientation (point absorber, attenuator, terminator, and oscillating wave surge converter) [42]. Two broad biomimetic classes are considered: single-feature-mimicking devices, which imitate one dominant biological trait, and multi-feature-mimicking devices, which combine several biological influences into a complete design, as shown in Table 1. The working-principle taxonomy of all WEC types, including those with biomimetic analogies, is presented in Fig. 3. This dual framing allows the review to assess biomimetic design analogies while maintaining compatibility with standard engineering classification conventions.

4.1.1. Mimicking the single feature

Single-attribute BWECS mimic one dominant biological feature of a marine organism. They are typically of simpler design with the aim of extracting energy efficiently in a narrow band of wave conditions. Although they are more straightforward to simulate and produce, such devices may prove to be less flexible in terms of the range of sea states and wave frequencies that they can cope with [12,72,73].

4.1.2. Mimicking multi-features

Multi-feature BWECS are capable of integrating two or more biological characteristics such as geometry, motion, or operating principles [12,13]. This combination solution adapts better and absorbs more energy in a wider window of waves but increases the complexity of design, control strategies and maintenance [74,75].

4.2. Working principles, architectural configurations, and PTO systems

BWECS transduce wave energy into a mechanical movement, imitating certain biological rhythms but adjusting their design according to the conditions of deployment [75,80]. The principle of motion design explains the rate of energy extraction, while the architectural layout and the PTO design are defined according to the best survival, maintainability, and the closest fit to the local wave climate [81,82]. Utilizing these design parameters, devices can be engineered for high energy capture in a wide range of wave climates [83]. Consequently, an integrated summary of the working principle, structure, and PTO system of representative BWECS is given in Table 2.

4.3. Deployment environments for BWECS

BWECS tend to perform best when the environment in which they are deployed matches the natural environment of their biological analogs [12]. Nearshore areas less than 20 m promote benthic or rooted designs, such as kelp and oysters, with easier access and synergy with coastal protection but with the least wave energy potential [91,92]. Intermediate depths (20–50 m) are conducive to floating or semi-submerged designs based on jellyfish and duck-like shapes, which offer

Table 2
Working principles, architectural configurations, and PTO systems of representative BWECS.

Principle	Description	Architectural configuration	PTO system	Example BWECS	References
Oscillating surge motion	Back-and-forth motion inspired by shells or kelp	Nearshore, seabed-mounted, semi-submerged	Hydraulic motors/turbines	Oyster, bioWAVE	[84,85]
Heave motion	Vertical pulsation of floating organisms	Floating, semi-submerged	Linear electrical generators	Jellyfish	[34,86]
Pitch motion	Angular oscillation similar to floating birds	Floating, surface-piercing	Rotary generators	Salter Duck	[87,88]
Bulge-wave propagation	Pressure pulse transmission mimicking cardiac systems	Submerged offshore	Hydraulic/rotary generators	Anaconda	[80,89]
Overtopping	Water elevated and stored before power extraction	Floating, surface-piercing	Low-head-hydro turbines	Wave Dragon	[53]
Attenuator motion	Relative motion between articulated segments	Floating offshore	Hydraulic pistons/rotary generator	Pelamis	[34,90]

Table 3
Deployment characteristics of representative BWECS.

Device	Biological analog	Depth (m)	Install. type	Install. Pos.	Max Power (kW)	Wave Power	Location	Environ. impact	Maintenance	Manufacturability	Ref.
Oyster	Oyster/kelp	10–15	Fixed	Seabed	800	Low-mod.	Nearshore	Medium	Med-Low	Good	[12]
bioWAVE	Kelp	6–23	Fixed	Seabed	1000	Low-mod.	Nearshore	Low	Medium	Medium	[12]
Jellyfish	Jellyfish	Offshore	Floating	Surface	600	Moderate	Offshore	Low	Low	Good	[12]
Salter Duck	Duck	2–30	Floating	Semi-subm.	375	Moderate	Offshore	Low	Medium	Med-Poor	[12]
Anaconda	Snake/heart	20–70	Floating	Submerged	1000	High	Offshore	Low	Medium	Medium	[12]
Wave Dragon	Dragon	20–30	Floating	Surface	40	Moderate	Offshore	Low	Med-Low	Med-Poor	[12]
Pelamis	Sea snake	50–60	Floating	Surface	1000	High	Offshore	Low	Low	Good	[12]

a compromise between power harvesting and survival complexity [12, 93]. Deep offshore which is greater than 50 m, flexible, elongated designs such as Pelamis and Anaconda can take advantage of high-energy wave climates but at a higher cost for installation and maintenance [80]. In every zone, compliant biomimetic structures have significantly better survival in random seas over their rigid hull counterparts, demonstrating that successful environment–biology pairing is critical in site selection [12,94]. Some representative biomimetic devices and their associated deployment environments are synthesized in Table 3.

4.4. Oyster: A biomimetic wave energy converter

Oyster, a BWECS, mimics the robust survival strategies of marine organisms like oysters and kelp [84,95]. Positioned in the nearshore environment (depths of 10–20 meters), Oyster captures wave energy by leveraging the horizontal surge motion of the waves, making it highly efficient in shallow coastal zones [84]. Unlike traditional rigid devices, Oyster's compliant design allows it to adapt to varying wave conditions, offering broad bandwidth energy capture and enhanced survivability in irregular seas [84]. Its bottom-hinged flap oscillates with wave motion, converting kinetic energy into hydraulic power through double-acting cylinders, which is then transmitted via subsea pipelines to an onshore hydroelectric station [84].

Oyster excels in nearshore conditions where wave energy is more directional and less intense than offshore, offering a cost-effective and reliable solution [84]. Its ability to decouple during extreme waves,

combined with its simple onshore power conversion system, makes it a safer and more manageable option than traditional offshore devices [84]. Moreover, Oyster's low maintenance and environmentally compatible design are significant advantages in the renewable energy sector [84].

4.5. Quantitative engineering characteristics of BWECS

While biological inspiration provides design intuition, a quantitative evaluation of hydrodynamic efficiency, scaling effects, and structural constraints is required to convert biomimetic concepts into realizable engineering constructs. Furthermore, this analysis describes the main engineering differences that distinguish BWECS from conventional rigid WECs, and defines quantitative criteria relevant to deployment in the Malaysian coastal environment.

4.5.1. Hydrodynamic performance

The CWR is the principal dimensionless metric for the hydrodynamic efficiency of WEC, defined as the ratio of absorbed power to incident wave power per unit crest width [96]. Table 4 delineates the reported CWR ranges, appropriate wave period intervals, and structural attributes for exemplary BWECS types. A key observation from Table is that while conventional point absorbers can theoretically achieve CWR up to 50% at resonance, biomimetic compliant designs consistently deliver CWR across a broader frequency bandwidth — a critical advantage for the irregular, broadband, short-period wave spectra of Malaysian coastal waters where a single dominant wave period cannot be reliably

Table 4
Quantitative performance and structural characteristics of representative BWECS.

BWEC type	CWR range (%)	Optimal T_p (s)	Scaling law	Key structural constraint	Ref.
Oyster/bioWAVE (flap-type OWSC)	15–40	6–12	$P \propto L^3$; $T \propto L^{0.5}$	Hinge fatigue; seabed anchoring at 10–20 m	[84,85]
Jellyfish-inspired (heaving body)	10–25	4–8	$D_{\text{opt}} \approx \frac{gT_p^2}{2\pi^2}$	Membrane fatigue; $\sim 10^8$ – 10^9 load cycles	[75,94]
Salter's Duck (pitching)	20–35	8–14	$P \propto L^2$	Spine bearing; gyroscope coupling	[87,88]
Anaconda (bulge-wave)	15–30	7–12	$P \propto L \times D^2$	Rubber tube fatigue; pressure cycling	[80]
Pelamis (attenuator)	7–15	7–14	$P \propto W^2 \times L_{\text{seg}}$	Joint seal integrity; multi-body coupling	[90]
WaveStar (multi-float)	20–35	4–10	$P \propto N \times r^3$	Float arm fatigue; PTO synchronization	[75]

assumed [96]. Biomimetic configurations also have good hydrodynamic constants. Compared to rigid bodies, compliant structures generally have smaller added mass $A(\omega)$ and larger radiation damping $B(\omega)$, which implies less reactive power demand and better performance in random seas [12,97].

4.5.2. Scaling laws and Malaysian site implications

Scaling laws govern how BWEC performance changes with device size and deployment wave climate. For surge-dominated flap devices following Froude scaling, power output scales as $P \propto L^3$ and natural period as $T \propto L^{0.5}$, where L is the characteristic flap dimension [84]. For Malaysian nearshore deployment where $T_p = 4$ – 8 s, these relationships imply optimal flap heights of 3–8 m at installation depths of 10–20 m — consistent with the Oyster device's operational envelope [84].

For heaving point absorber-type BWECS, the optimal diameter for resonance at a target wave period is:

$$D_{\text{opt}} \approx \frac{g T_p^2}{2\pi^2} \quad (1)$$

yielding diameters of 2–9 m across the Malaysian wave period range [96]. However, the $\pm 40\%$ seasonal variation in dominant period between northeast monsoon and inter-monsoon conditions means that a device optimized for monsoon conditions will operate significantly off-resonance for several months per year, underscoring the need for active tuning or broadband compliant designs rather than fixed-geometry resonant devices [83,84].

4.5.3. Structural constraints

Compliant BWEC structures — including the rubber tube of the Anaconda and the flexible membranes of jellyfish-inspired devices — must withstand cyclic fatigue loading over a 20–25 year design life, corresponding to approximately 10^8 – 10^9 load cycles [80,94]. Material selection must simultaneously satisfy three competing requirements: sufficiently low elastic modulus for large deformation under small wave amplitudes; adequate fatigue resistance under broadband cyclic loading; and chemical resistance to ultraviolet degradation, biofouling, and tropical saltwater corrosion. For Malaysian nearshore deployment, high suspended sediment concentrations during monsoon-driven currents introduce additional abrasive wear on flexible surfaces that conventional North Atlantic WEC material specifications do not address [94]. These structural demands are substantially more complex than those of conventional rigid steel WECs, and quantitative fatigue life prediction under Malaysian site-specific loading spectra remains an open engineering challenge — one where data-driven condition monitoring frameworks, discussed in the research gaps section, provide essential operational support.

5. Wave energy in Malaysia

Malaysia's wave energy resource is spatially and seasonally distributed among offshore, strait, and coastal waters, with stronger wave power mostly occurring in the deeper offshore areas facing the South China Sea, especially in the northeast monsoon season [98]. The wave power resource is higher in the offshore area than in the nearshore areas, but the wave energy in the straits, such as the Strait of Malacca, is significantly lower [99]. Coastal regions like the east coasts of Peninsular Malaysia and East Malaysia have moderate but seasonally intensified wave energy resources, which are feasible for low-capacity WEC installation. Fig. 4 shows how these different energy regimes are spread out across Malaysia's main maritime zones. The wave power density values are based on published research, and the figure gives a qualitative overview of the offshore-to-nearshore gradient and the seasonal effect of the northeast monsoon.

5.1. Sea/Offshore Zones

The Malaysia's Sea/Offshore Zones (including the South China Sea — SCS offshore Sabah and Sarawak, and the Luzon Strait) are also the highest-energy wave exploitation areas [100,103,104]. These areas have a deep and complex bathymetry, ranging from shallow continental shelf depths of approximately 0–200 m to more than 3000 m in the Luzon Strait, and also were modulated by islands, seamounts, and submarine canyons [105]. The wave energy availability is high with the average wave power of the Luzon Strait region ranging from 2 to 40 kW m^{−1} and the northern SCS region having the average wave power of more than 20 kW m^{−1} [98,100]. The wave power density could be as high as 330 kW m^{−1} in the Luzon Strait and 35 kW m^{−1} in the northern SCS during the peak winter months [101,106]. Seasonal variations are significant, with the highest energies in the northeast monsoon/winter and the lowest in summer and spring. In particular, wave heights in these offshore regions range in an average between 0.7 and 2.4 m, with occasional extreme wave heights of up to 11.3 m, and wave periods are usually from 5 to 8 s, increasing in winter and autumn [101,107,108]. The high energy availability in such regions makes them suitable for the installation of more robust WECs such as point absorbers, oscillating water columns, and deepwater devices, or wave farm devices like Wave Dragon [98,101,106]. However, there are challenges, such as harsh conditions like typhoons and intra-annual variation of wave power, that necessitate both appropriate siting and engineering solutions [109]. Nevertheless, just from the offshore perspective, the prospects for renewable energy exploitation on a massive scale in Malaysia appear bright [109,110].

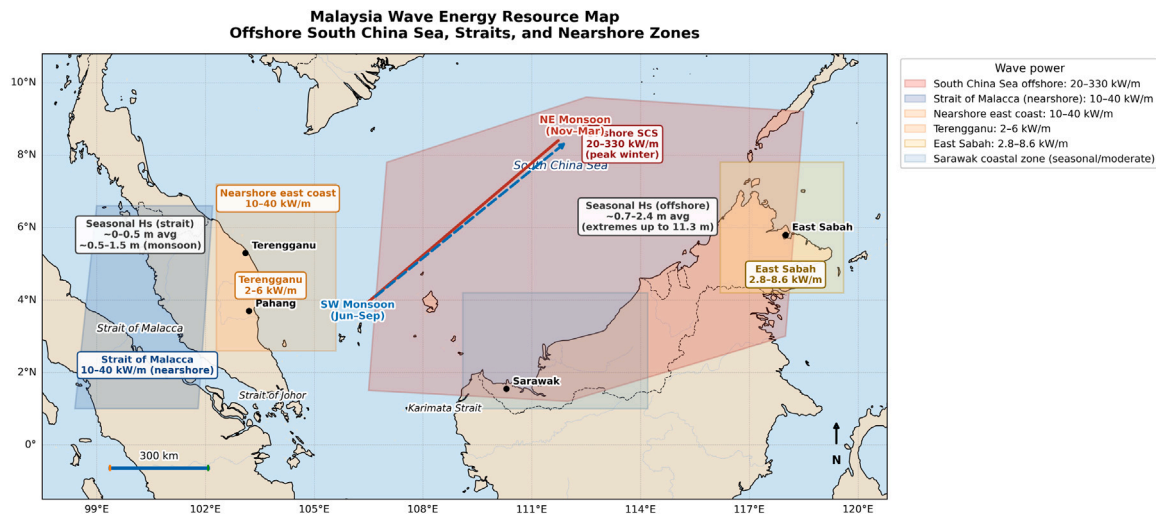


Fig. 4. Wave energy resource map of Malaysia showing offshore, strait, and nearshore coastal zones with approximate wave power densities derived from literature [98–102].

5.2. Strait/channels

Hydrodynamic conditions of straits and channels within Malaysia's territorial waters vary and determine their feasibility for marine energy exploitation [111]. The Strait of Malacca is a nearshore channel of the continental shelf with a depth between 25 and 59 m and has strong tidal forcing, sediment transport, and monsoon-induced current, which acts as a barrier to wave energy flux and causes frequent depth variations [112,113]. Wave energy potential is generally constrained here, where nearshore wave power is within the broad range of 10–40 kW m^{-1} , while farther offshore, in the deeper sea regions such as the South China Sea, wave power can be as high as 500 kW m^{-1} [15]. The oceanographic setting: strong seasonality is produced by the tropical monsoon system; the southwest monsoon (June–September) brings southwesterly winds and a relatively calm sea state, while the northeast monsoon (November–March) is manifested by strengthened wave activity. Significant wave heights in the strait are mostly low (averaging 0–0.5 m) but rise to 0.5–1.5 m under the monsoon influence, with maximal heights up to 3–5 m recorded in particular cases [114,115]. The Strait of Johor is another example of Malaysian straits, which are tidal and current dominant, with basically no useful wave energy, but more viable to harvest tidal or current energy due to their minimal width and sheltered nature [116]. Broad straits like the Karimata Strait and deep channels such as the Sibutu Passage can be subjected to the modulated wave–current systems and intensified energy regime as a result of inter-basin flux and regional circulation patterns [117,118].

5.3. Coastal/nearshore zone

The wave energy potential for extraction along the coastline of Malaysia, specifically Terengganu, Pahang, and East Sabah, is moderate to high. The depth of the Terengganu coast reaches 200 m; the hydrodynamics of coastal upwelling and monsoon-driven currents are continually shaped by interactions with the bottom topography, resulting in an enhanced wave energy potential in the northeast monsoon season; wave power varies from 2 to 6 kW m^{-1} , and average wave heights are between 0.5 m and 2 m [102]. The wave period ranged from 2.76 to 5.28 s, with the maximum wave period of 3.94–8.28 s, which is favorable for nearshore WEC deployment, although the achievability of WEC technology during the off-monsoon season was limited [102]. Pahang also has similar coastal features, including similar hydrodynamic and seasonal wave energy influence, although some detailed wave and periods data are missing. Being open to the South China Sea, East Sabah has a typical wave power of 2.8–8.6 kW m^{-1} at moderate depths which

indicates the feasibility of WEC deployment in this region, probably more so for the smaller technology (1–2 MW) [99]. The three locations, Terengganu, Pahang and East Sabah, are also readily accessible, not too far from ports and grid connection infrastructure, and have relatively predictable monsoon-driven wave climates, further enhancing technical feasibility [102]. Constraints are the reduction in energy density during non-peak monsoon times; the shallow waters will restrict certain types of WECs, as well as potential conflicts with other maritime activities and with related sensitive marine ecosystems such as coral reefs and mangroves [67]. In summary, these shorelines provide a seasonally acceptable offshore wave energy resource, which may be utilized to power a pilot/small WEC system.

5.4. Wave climate statistics and device suitability for Malaysian waters

The preceding zone-specific descriptions reveal a low-energy, highly seasonal wave climate that imposes distinct engineering constraints on WEC selection and design. Table 5 consolidates the key statistical wave parameters — significant wave height (H_s), energy period (T_e), and mean wave power density (P) — across the three principal Malaysian maritime zones, derived from ERA5 reanalysis, SWAN hindcasts, and regional buoy records [98,100–102,115]. Significant wave heights in nearshore areas rarely exceed 2.0 m (95th percentile ≈ 1.8 m), with peak periods of 4–8 s and energy periods of 3–6 s. The resource is strongly modulated by the northeast monsoon (November–March), when H_s and power density increase by 2–4 times compared with inter-monsoon calm periods [99,102].

These low-energy, short-period conditions render many conventional WEC designs suboptimal for Malaysian deployment. The deployment characteristics of representative BWECs summarized in Table 3 provide the basis for the following suitability assessment. For Malaysian nearshore zones (depth 10–20 m, $T_e = 3$ –6 s), oscillating wave surge converters (OWSCs) of the Oyster and bioWAVE type represent the most suitable architecture: their surge-dominated response matches the directional character of Malaysian nearshore waves, they operate effectively at 6–23 m depth, and their compliant design provides broadband energy capture across the variable monsoonal spectrum [12,84]. Point absorbers with resonance diameters of 2–5 m are similarly compatible, as their natural period can be tuned to the 4–8 s dominant energy period range through active control or geometric adaptation [96]. Fixed OWC devices are applicable in directional nearshore settings provided impulse turbines are selected to handle the short, irregular Malaysian wave periods, as discussed in Section 3 [46]. In contrast, attenuator-type devices such as Pelamis and terminator devices such as Wave

Table 5

Wave climate statistics and device suitability by Malaysian coastal zone.

Zone	Mean H_s (m)	Dominant T_e (s)	Mean P (kW m^{-1})	Recommended device types	Primary constraints	References
East Coast Peninsular (Terengganu, Pahang)	0.8–1.2 (mean); up to 2.0 (NE monsoon)	4.0–6.5	2–6	Nearshore OWC; low-draft point absorbers; Oyster-type OWSC	Low inter-monsoon energy; resonance mismatch at short T_e	[102]
East Sabah (open SCS)	1.0–1.8 (mean); up to ~4.0 (extreme)	5.0–8.0	2.8–8.6	Oyster-type OWSC; semi-submerged point absorbers; small OWC arrays	Typhoon exposure; biofouling; limited grid infrastructure	[99]
Strait of Malacca (nearshore)	<0.5 (non-monsoon); 0.5–1.5 (monsoon)	3.0–5.0	<2	Not viable for conventional WECs; only micro-TENG or hybrid tidal-wave	Insufficient wave energy density; heavy shipping	[15,114,115]
South China Sea Offshore (>50 m)	1.5–2.4 (mean); up to 11.3 (extreme)	6.0–10.0	20–330	Attenuators (Pelamis-type); large point absorber arrays; overtopping devices	High installation/O&M cost; typhoon survivability; distance to shore	[100,101]

Dragon are optimized for long-period ($T_e > 8$ s), high-energy offshore swells and significantly underperform in the Malaysian short-period nearshore regime [98]; these architectures are only viable for the high-energy offshore SCS zone. The Strait of Malacca is categorically unsuitable for wave energy extraction at current technology readiness levels due to its sub-2 kW m^{-1} mean power density [15]; tidal and current energy technologies represent a more viable harvesting pathway in this zone. The large seasonal power ratio across all nearshore sites — NE monsoon peak to inter-monsoon minimum ranging from approximately 3:1 to 8:1 [99,102] — further reinforces the preference for biomimetic compliant designs whose broadband frequency response and structural flexibility allow effective operation across both monsoonal and inter-monsoon conditions, unlike narrow-band resonant rigid WECs.

The unique Malaysian wave climate, with mild significant wave heights, short peak periods and strong monsoonal variation, imposes particular hydrodynamic and operative issues to BWECS [102]. The low-energy, highly variable nearshore conditions contrast significantly with the high-energy, long-period swells that form the basis of most current WEC designs and modeling standards, making traditional analytical, physics-based, and empirical methods inadequate for precise performance forecasting and site-specific optimization [98]. Precise and computationally efficient models are necessary for converting local resource assessments into dependable power-output predictions, structural-load evaluations, and adaptive management strategies specific to Malaysia's coastal waters [119]. This section systematically examines the range of modeling methodologies for BWECS, advancing from traditional analytical and deterministic approaches to sophisticated numerical, statistical, and, importantly, data-driven machine learning techniques appropriate for the nonlinear, non-stationary dynamics of monsoon-affected tropical seas [120].

6. Modeling approaches for WECs

Wave energy generation modeling is the time series estimation of the WEC electrical power output under realistic wave conditions for the purpose of performance evaluation, design optimization, cost reduction, and large-scale deployment [96,119,121]. Accurate modeling is paramount because the converters need to be designed to be efficient in all sea states over their relatively long operating life to make the levelized cost of energy competitive [96,122]. This problem is difficult because of extremely nonlinear hydrodynamics, strong temporal wave variability, and multiple converter configurations [75,96,122]. The existing methods can be roughly categorized into analytical and physics-based hydrodynamic models, numerical and CFD-based simulations, statistical time series models, and empirical power-matrix models for energy yield estimation [96,119,122]. In recent years, data-driven and machine-learning models have been introduced as a complement to these methods to improve forecasting, control, and optimization [27, 120].

6.1. Analytical model

Analytical models are the simplest level of modeling of wave energy production and are based on linear wave theory and have been used to predict theoretical resource potential and first-order device response given H_s , T_p , fluid density, and g from significant wave height, wave period, fluid density, and gravitational acceleration [119,123]. Due to their closed form and minimal computational cost, these models are also extensively employed in wave climate evaluation, initial site screening, and concept design activities, in which the long-term behavior over thousands of hours of operation needs to be investigated in a computationally efficient manner [122]. In the case of BWECS, fluid dynamics models are often combined with low-order mechanical oscillators or hydro-elastic beam and plate models for the representation of device motion and the calculation of the power absorbed in regular or weakly nonlinear waves [123]. Their transparency and simplicity also render them desirable for control-focused analysis and conceptual wave-to-wire modeling [124,125]. However, the analytical and linear potential flow models involve restrictive assumptions, such as small amplitude motion, inviscid and irrotational flow, and linear free surface [96,122]. Comparisons to experimental data and nonlinear CFD solutions show that these models overpredict motion and power and ignore significant nonlinear processes such as viscous drag, wave breaking, and large-amplitude structural response [96]. As a result, they are used mainly as baseline or conceptual models and are being supplemented by higher fidelity numerical and data-driven methods in advanced BWECS design [119].

6.2. Deterministic/physics-based models

Deterministic or physics-based models constitute the core of WEC analysis and design, as they model fluid–structure interactions using first-principles hydrodynamics [97]. These models generally originate from radiation–diffraction potential-flow theory, which is solved by applying BEM (i.e., WAMIT, NEMOH, or AQWA) that delivers frequency-dependent added mass, radiation damping, and excitation forces for each mode of motion (heave, surge, and pitch) [97,126,127]. The hydrodynamic coefficients are next transformed into Cummins-type integro-differential or equivalent finite-order state-space models, where total loads are split into excitation, radiation with memory, and hydrostatic restoring forces [97,128,129]. Finite-order approximations provide computationally efficient time-domain simulations that are appropriate for device trajectory estimation, absorbed power assessment, array interactions, and control-oriented analysis [128,130]. Reduced-order deterministic models have been demonstrated to match CFD or experimental results with errors below a few percent, while incurring orders of magnitude lower computational cost [128,129]. However, the accuracy of deterministic models is highly dependent on the quality of the BEM preprocessing and the handling of viscous or strongly nonlinear effects, which may be the dominant source of damping and

power dissipation in severe environments [122,126,131]. Therefore, they are still the workhorse for BWEC design and control, although they are often modified (with Morison drag terms, tuned damping, etc.) in order to provide trustworthy predictions [128,131]. The Cummins-type time-domain formulations and frequency-domain boundary element method models provide the hydrodynamic coefficients — added mass, radiation damping, and wave excitation forces — that function as training targets and inherent physical constraints for the data-driven surrogate models discussed in the subsequent section. This direct linkage between physics-based hydrodynamic modeling and data-driven learning underpins physics-informed machine learning methodologies, wherein governing equations are integrated as constraints during model training instead than being solved directly.

6.3. Numerical, CFD, and spectral wave models

Numerical and CFD simulations treat fluid flow by discretizing the Navier–Stokes equations in space and time with finite-volume or finite-element schemes to solve for velocity, pressure, and free-surface information [132,133]. In wave energy applications, CFD is typically performed via numerical wave tanks using two-phase RANS/URANS and VOF-like methods to capture nonlinear wave propagation, viscous dissipation, turbulence, wave breaking, and fine-level wave–structure interaction around rigid and biomimetic devices [132,134–136]. In the case of flexible or articulated BWECs, CFD is coupled with finite-element solvers in fluid–structure interaction (FSI) models to capture large deformations, internal stresses, and hydroelasticity [137,138]. At greater spatial scales, the spectral wave models WAVEWATCH III and SWAN are used to represent the regional and coastal wave climate by numerically solving the wave action balance equation, including the parameterized source terms, which have shown good performance in hindcast and operational forecast for marine and coastal applications [139]. Nevertheless, these spectral models are phase-averaged and therefore lack the ability to resolve nonlinear device-scale loads, PTO dynamics, or detailed wave–structure interactions and must be down-scaled or coupled to local hydrodynamic models for BWEC study [132, 139]. Even if CFD can replicate motion and loading with typical errors in the order of 2%–10% and is more accurate than the coupled spectral–numerical system, both are penalized by extremely large computational costs due to the necessity of using very fine meshes and very small time steps, rely on high-performance computing, and are limited in scalability [132,140]. These constraints render the long-term energy production estimation, real-time control, and large-scale parametric optimization unrealistic [135,137]. Data-driven, ML/DL-based, and more recently, transformer-based surrogate models overcome these limitations by learning fast emulators from CFD or multi-fidelity data, achieving near-CFD accuracy with several orders of magnitude reduction in computational cost [141,142].

6.4. Statistical models

Statistical models define the quantitative relationship between wave characteristics and WEC power output based on historical or measured data [25,27]. Linear and nonlinear regressions, probability distributions (e.g., Weibull and Rayleigh), and time-series models (ARMA, ARIMA) are among the most popular tools for resource evaluation and short-term prediction [27,143,144]. These models are computationally inexpensive, easy to implement, and suitable for long-term energy prediction, as they yield the probability density functions, power spectral densities, and the average absorbed power [27,145,146]. Statistical linearization has been used for approximating nonlinear WEC dynamics, which makes it possible to quickly estimate response statistics for different sea states and device types, such as point absorbers, oscillating wave surge converters, and oscillating water columns [25, 145,147]. Nevertheless, these techniques come with an implicit assumption of linearity and stationarity, which hinders their capability of

capturing intense nonlinearities, nonstationary sea states, and extreme wave events, leading to poorer prediction performance in time-varying marine environments [25,143,145,148]. Moreover, design optimization and control-oriented prediction may also be limited by such simplifying assumptions [27]. These constraints encourage the use of machine learning and deep learning models that are able to learn intricate, nonlinear, time-varying relations from data directly [25,27,149]. Data-driven approaches such as neural networks, Gaussian processes, and hybrid statistical-ML frameworks provide superior forecasting, uncertainty quantification, and surrogate modeling capabilities and can be viewed as a complement to conventional statistical methods by rectifying some of the major limitations of the latter [25,27,143,149].

6.5. Empirical/power-matrix models

Empirical or power-matrix models are commonly employed for performance evaluation of WECs, since they establish an immediate relationship between the observed or modeled sea states, usually characterized by significant wave height and wave period, and the mean output electrical or mechanical power [150–152]. These models are often provided in the form of lookup tables or matrices, allowing quick calculation of the annual energy production and device performance comparison without performing detailed hydrodynamic simulations [150–152]. Power matrices are typically formed by choosing representative sea states from a site-specific wave scatter diagram, calculating the absorbed power for each state with time-domain or spectral wave-to-wire simulations, and arranging the results in a probability-weighted matrix [151,153]. Surrogate modeling techniques like Kriging plus active learning strategies have further alleviated the computational cost while preserving high reconstruction accuracy [150]. For all their practical success, they tend to be very site-specific and device-specific and have little generalization power [152]. They reduce the complexity of the wave spectrum, ignore the intra-class variability of each sea state, are based on stationary hypotheses, and poorly model nonlinear or strongly coupled system mechanics [150,154]. Consequently, their predictions for blind sea states, modified device configurations, or different control schemes cannot be considered reliable [153]. Data-driven and ML approaches address some of these issues by learning nonlinear relationships directly from data, implicitly modeling high-order interactions among variables, providing accurate predictions even outside the region of original training data information, and even being computationally tractable [25,155].

Table 6 reveals a fundamental trade-off: physical fidelity and computational cost scale together, while no single method dominates across all modeling objectives. Physics-based methodologies provide incremental improvements in accuracy; however, they have been predominantly verified for high-energy, long-period wave situations, hence constraining their direct relevance to Malaysian short-period, low-amplitude scenarios. Statistical and empirical models exhibit computational efficiency; nonetheless, they presuppose stationarity, a criterion consistently contravened by Malaysia's monsoon-influenced wave climate. Machine learning models offer superior nonlinearity capture and computational efficiency, yet all high-performing models were trained on North Atlantic or Australian data, and their transferability to Malaysian conditions remains unvalidated. The optimal strategy is therefore a hybrid framework combining BEM-derived hydrodynamic structure with physics-informed or transfer-learning-adapted ML models to handle Malaysian data scarcity and seasonal variability.

7. Key input features for predictive modeling

The prediction of BWEC performance needs a suitable set of parameters, representing the wave environment, the site description, the device configuration, and the energy conversion mechanism [27,119, 157,158]. These parameters define the quantitative relationship between ocean state and device response, which can be used for numerical

Table 6

Comparative assessment of WEC modeling approaches with applicability to Malaysian coastal conditions.

Modeling approach	Physical basis	Typical accuracy	Key limitations	Nonlinearity capture	Computational demand	Long-Term simulation	Suitability for Malaysian conditions
Analytical/Linear Wave Theory	Linear potential flow; Froude–Krylov excitation; small-amplitude wave assumption	$\pm 20\%$ – 40% error vs. experimental data for WEC power in irregular waves [96,122]	Assumes small amplitude, inviscid, irrotational flow; overpredicts motion and power; ignores viscous drag and wave breaking; invalid under energy-maximizing control	Very low	Very low (seconds)	High	The nearshore waters of Malaysia exhibit brief peak periods ($T_p = 4\text{--}8\text{ s}$) characterized by irregular, multi-directional, monsoon-induced waves, leading to an overestimation of WEC responsiveness and power by linear wave theory. Appropriate solely for preliminary resource evaluation and conceptual sizing, not for performance forecasting at deployment locations.
Deterministic/Physics-Based (BEM + Cummins)	Radiation–diffraction potential flow; BEM solvers (WAMIT, NEMOH, AQWA); Cummins integro-differential equation for time-domain motion	Errors below 5% – 10% vs. CFD for moderate sea states [128,129]; degrades under strongly nonlinear conditions	Viscous drag not inherently captured; Morison correction terms required; linear superposition breaks down at large amplitudes; BEM preprocessing is labor-intensive	Moderate (with viscous correction)	Moderate (minutes to hours)	Moderate	BEM-based Cummins models suit Malaysian nearshore OWSC and point absorbers at $10\text{--}20\text{ m}$ depths, where H_s is usually below 2.0 m and small-amplitude assumptions hold during inter-monsoons, though viscous drag corrections matter at low device velocities when $H_s < 1.0\text{ m}$.
Numerical/CFD (RANS, VOF, FSI)	Full Navier–Stokes equations; two-phase RANS/URANS with VOF free-surface; FSI coupling for flexible BWECS structures	2% – 10% error for forces and motions vs. experiments [132,140]	Extremely high computational cost (days–weeks); requires HPC; not scalable for long-term energy production; labor-intensive mesh generation	Very high	Very high (days–weeks)	Very low	Malaysian short-period, irregular waves cause nonlinear wave–structure interactions unresolved by linear models, making CFD essential for validating BWECS, especially jellyfish-inspired membranes and Anaconda tubes requiring FSI, but computational cost makes it impractical for forecasting or long-term energy-yield assessment at Malaysian sites.
Statistical (ARMA, Weibull, regression)	Statistical relationships between wave climate parameters and WEC output; probability distributions; time-series regression	$R^2 = 0.70\text{--}0.90$ for wave resource estimation [143,145]; degrades for nonstationary/extreme events	Assumes linearity and stationarity; cannot capture strong nonlinearities or monsoon-driven variability; limited predictive horizon	Low–moderate	Low (seconds)	High	Malaysian waves are non-stationary due to northeast (November–March) and southwest (June–September) monsoons, with $H_s = 0.5\text{--}2.0\text{ m}$ and ENSO-linked interannual variability; thus ARMA/regression stationarity assumptions fail, limiting WEC prediction beyond annual means, though resource averages and monsoon-transition dynamics remain partly characterized.
Empirical/Power Matrix	Lookup tables of mean power vs. (H_s , T_p) from simulations or experiments; probability-weighted AEP calculation	Errors of 15% – 30% for off-design sea states [151,152]	Site- and device-specific; ignores spectral variability; stationary assumption; unreliable for modified configurations or control schemes	Moderate (empirically embedded)	Very low (seconds)	Very high	Power matrices are practical for Malaysian WEC site comparison using ERA5 and hindcast scatter diagrams, but full-year calibration misestimates seasonal performance; separate monsoon and inter-monsoon matrices, calibrated with local measurements, are recommended for accurate Malaysian coastal AEP assessment.
Machine Learning/Deep Learning	Data-driven function approximation; learns nonlinear input–output mappings from historical or simulated data	$R^2 = 0.89\text{--}0.99$ (ensemble) [25,155]; $R^2 > 0.99$ (hybrid LSTM) [21,156]; RMSE reductions 60% – 90% vs. statistical baselines	Requires large datasets; risk of overfitting; poor extrapolation; black-box models; performance degrades for unseen sea states; no guarantee of physical constraints	High	Low after training (milliseconds); high during training	High	Malaysian coastal waves are nonlinear, non-stationary, and seasonal, favoring ML over statistical/empirical models, but reviewed high-performing ML used NOAA NDBC, UCI, or ERA5 — not Malaysian data — so application requires domain-adaptation, transfer learning, or local fine-tuning; PINNs are most promising.

simulation, as well as for data-driven modeling leveraging machine learning (ML), deep learning (DL), or Transformer frameworks [27]. Selecting the correct parameters is essential, as the predictive models learn the relationships from the data and do not explicitly solve the physics [159]. In the case of oyster-type BWECS in nearshore Malaysian waters, the inputs shall include the dominant wave drivers, bathymetry and spatial context, meteorological conditions, device geometry, and PTO parameters [12,27]. Power generation, efficiency, and operational

viability are measured by outputs [119]. Previous research shows that among the numerous parameters that can be considered, e.g., wave height, wave period, water depth, flap size, and PTO damping, only a few consistently dominate the prediction of performance [27,72]. As a result, combining these parameters into a single wave–spatial–temporal dataset enables ML models to capture site-specific energy conversion processes and to extrapolate to the conditions of maximum energy extraction [160].

7.1. Input parameters

Input parameters correspond to the features, which are used by the predictive models to describe the environmental, site, and operational conditions of a WEC [27]. These variables describe the wave resource, the nearshore environment, and the device configuration in a quantitative sense and serve as inputs to the energy conversion process in predictive modeling [161]. The magnitude of accessible energy is determined by wave-related factors, which also specify the time, directionality, and intensity of incoming waves [146]. Spatial and bathymetric parameters describe the location of the deployment site and incorporate nearshore transformation processes, including shoaling, refraction, and attenuation [162]. The temporal descriptors account for seasonal and year-to-year changes in wave climates, which are important for monsoon-dominated areas [146]. Meteorological inputs contain supplemental details on atmospheric forcing for wave generation [163]. Device- and PTO-specific parameters describe the mechanical dynamics of the converter and the transformation of motion into energy [162]. Taken as a whole, these input parameters allow data-driven models to represent the nonlinear mapping from ocean and device states to energy conversion performance. Table 7 provides an overview and commentary on the prevalent wave, bathymetry, and meteorological and temporal parameters found in the literature, respectively.

7.2. Strategies for preprocessing non-stationary wave records

Multi-decadal reanalysis products such as ERA5 and WAVEWATCH III embed superimposed variability from intra-seasonal monsoon cycles, inter-annual ENSO teleconnections, and long-term climate trends, each of which can systematically bias deep learning model training if left unaddressed. Long wave records are appropriately modeled as a time-dependent deterministic component superimposed on a stationary stochastic residual, with decomposition methods serving to isolate the latter prior to model ingestion [164]. For Malaysian waters, where northeast and southwest monsoon transitions generate abrupt distributional shifts in significant wave height and peak period, a hierarchical decomposition strategy is recommended. STL-based hybrid frameworks effectively separate trend, seasonal, and remainder components, with component-specific sub-models demonstrably outperforming single end-to-end networks on seasonal wave data [165]. For records exhibiting nonlinear trend evolution, EEMD and its adaptive variant CEEMDAN decompose signals into intrinsic mode functions without imposing stationarity assumptions; EEMD-LSTM hybrids applied to South China Sea records achieve RMSE reductions of 52%–66% relative to standalone LSTM baselines across 3–12 h horizons [166, 167]. Additionally, z-score normalization computed over a rolling seasonal window — rather than the full training record — prevents high-variance monsoon periods from dominating normalization statistics, preserving signal integrity across inter-monsoon regimes.

8. AI-based predictive modeling for BWECS

The analytical, computational fluid dynamics (CFD), and statistical models which were discussed in Section 6 have inherent constraints which restrict their usefulness for practical wave energy applications [180,181]. While high-fidelity CFD provides complete hydrodynamic modeling, its immense computational cost (days to weeks of simulation) precludes its employment for real-time control and operational decisions [26,182]. Simplified analytical models based on linear hydrodynamics also depend on restrictive assumptions, such as small-amplitude oscillations about an equilibrium point, which become invalid under energy-maximizing control policies [181,183]. Conventional ARX-type statistical models suffer from increasing errors as the horizon gets larger due to imperfect sea state estimates, giving rise to a modeling paradox: linear control actions based on linear theory drive

WECs into nonlinear regimes and hence result in power production that is lower than the predicted output [63].

By substituting equation-based models with data-based learning models, artificial intelligence (AI) and machine learning (ML) try to address these limitations [181,184]. The increasing availability of large-scale ocean data sets is well-suited for ML-based modeling [27]. Reanalysis products such as the ERA5 from the European Centre for Medium-Range Weather Forecasts provide multi-decadal wind and wave time series, while the National Oceanic and Atmospheric Administration buoy networks and numerical wave models such as SWAN provide complementary, high-dimensional training data [22,185,186]. These resources allow ML-based algorithms to uncover nonlinear and multivariate relationships that are not easily represented in an analytical form [186].

Such a transition is particularly relevant for biomimetic and multi-body WECs, as their intricate geometries and coupled power take-off systems produce multi-frequency responses and cross-coupled dynamics that are tedious to be modeled explicitly [187,188]. AI supports a wave-to-wire learning paradigm in which the behavior of the system is deduced straight from data, enabling concurrent optimization of power takeoff and structural loading [183,187].

Before reviewing individual AI/ML approaches, the quantitative benchmarking context must be established. Performance metrics — R^2 , RMSE, and MAE — are reported inconsistently across the wave energy ML literature: some studies report in-sample training accuracy rather than out-of-sample test performance, dataset sizes range from under 1000 to over 130,000 samples, and synthetic simulation data (JON-SWAP, WEC-Sim) are not always distinguished from measured ocean records [24,27]. To address this, Table 9 synthesizes the reviewed studies from Tables 6–8 into a structured comparative synthesis covering reported performance ranges, dataset characteristics, validation practices, and overfitting mitigation — enabling direct cross-category comparison. All R^2 values above 0.99 reported in this section should be interpreted as achievable under favorable single-site, stationary training conditions and are not assumed to generalize to Malaysian monsoonal conditions without local validation.

A closely related issue concerns the physical grounding of AI/ML models in WEC hydrodynamics. Wave energy conversion is governed by well-established physical principles: the Cummins integro-differential equation describes floating-body motion under wave excitation and radiation forces [97]; the theoretical maximum power capture is bounded by the capture width ratio (CWR), limited to $D/2\pi$ for a point absorber of diameter D [96]; and the wave-to-wire chain is subject to cumulative efficiency losses at each stage. A data-driven model predicting power beyond the CWR limit, or violating energy conservation, provides no engineering utility regardless of its R^2 . In Malaysian nearshore conditions, the CWR bound for a point absorber of diameter 2–5 m at $T_p = 4–8$ s limits theoretical peak power to approximately 5–15 kW per device—a physical reference that AI/ML models must respect, not exceed.

8.1. Taxonomy of AI/ML approaches in wave energy

Applications of machine learning in wave energy research cover a wide range of paradigms, such as supervised predictive modeling and unsupervised pattern discovery, as well as reinforcement learning-based control strategies [27,120,189]. Delivering a clear taxonomy of these methods is necessary for methodically associating individual AI/ML techniques with the related wave resource and WEC performance modeling tasks [27,120,186,190]. Thus, the prior arts may be categorized into three main learning paradigms — supervised, unsupervised, and reinforcement learning — which serve different purposes in terms of modeling and control of ocean engineering systems [27,120].

Table 7

Input features for BWEC predictive modeling: wave, bathymetric, meteorological, and temporal parameters.

Parameter	Typical range	Physical meaning	Importance for WEC modeling	Typical data sources
Wave parameters				
Significant wave height (H_s)	Continental shelf waters typically 0–10 m [168]; low-to moderate-energy locations below 1–2 m [169]; extremes reach ~12–18 m [170].	Standard deviation-based height of the highest one-third waves ($H_{1/3}$), describing random sea states [171].	Controls wave energy flux ($\sim H_s^2$) and structural loading; key input for resource and AEP assessment [172].	Long-term hindcasts (WWIII, SWAN, AusWAM, ERA5); NDBC and regional buoys [172].
Peak wave period (T_p)	Generally 4–12 s in semi-enclosed and coastal seas, rising to ~15 s in energetic swell conditions [173].	Period at spectral energy maximum, often used when full spectrum T_e is unavailable [172].	Used with H_s to compute wave power when T_e is unavailable; sets resonance with WECs [172].	Directional buoys; spectral hindcasts (SWAN, WWIII, MASNUM-WAM) [172].
Mean/energy period (T_m, T_e)	Approximately 6–11 s in active oceans, reducing to 2–6 s in calm seas [174].	Spectral weighted mean period, corresponding to an equivalent single-frequency wave of the same total energy [172].	Preferred period for power density estimation; lower bias than T_p -based formulas [172].	Spectral hindcasts; buoy spectral moments (m_0, m_{-1}) [172].
Wave direction (θ)	Unimodal or bimodal distributions depending on basin [173].	Mean or dominant propagation direction.	Affects directionality coefficient, array layout, and coastal shadowing [175].	Directional buoys; SWAN/WWIII archives [175].
Wave energy flux/power density (P)	Typical range 5–35 kW m ⁻¹ ; upper percentile values reach ~60–78 kW m ⁻¹ [174].	Energy flow per meter of wave crest [172].	Primary metric for site ranking and AEP estimation [172].	Derived from H_s and T_e/T_p ; some hindcast outputs P directly [172,175].
Wave spectrum $S(f, \theta)$	Site-specific; seasonal bandwidth and directional spreading [176].	Variance distribution over frequency and direction [176].	Required for hydrodynamic modeling, control design, and extreme statistics [176].	Spectral buoys; WWIII, WAM, SWAN hindcasts [176].
Bathymetric parameters				
Water depth (h)	Depths in nearshore studies typically 10–200 m [175].	Still-water depth.	Controls shoaling, breaking, survivability, and device type [175].	Nautical charts; bathymetric grids in SWAN/WWIII [175].
Distance to shore	Few km (nearshore) to tens-hundreds of km (shelf) [171,175].	Horizontal site distance from coastline.	Impacts cable cost, O&M, and depth-related attenuation [175].	GIS coastlines; project layouts; model grids [175].
Latitude/Longitude	Global domain -90° – 90° , -180° – 180° ; typical resolution 0.04–0.1° [173,175].	Geographic position of site [175].	Used to extract metocean series and generate maps [175].	ERA-Interim/ERA5; AusWAM; global WWIII [175].
Meteorological parameters				
Wind speed (U)	Wind velocity in nearshore areas normally 2–5 m/s, with increases during the northeast monsoon [177].	10-m wind driving local wind-sea generation.	Primary driver of wave climate and model forcing [175].	ERA5, CFSR, CCMP, buoys, WRF [175].
Wind direction	Often aligned with dominant wave direction [178].	Direction of wind flow.	Separates wind-sea from swell; useful in hybrid ML models [172].	Same as wind speed sources [175].
Temporal parameters				
Timestamp	Hourly or 3-hourly records over 20–40+ years [173].	Exact time of each sea state.	Required for time-series analysis and ML forecasting [172].	Hindcast archives; buoy logs [172].
Month/day of year	Clear seasonal patterns (winter maxima, summer minima) [173].	Intra-annual index.	Seasonal AEP and resource characterization [173,175].	Hindcast archives; buoy logs [172].
Year	20–70-year spans used for trend analysis [179].	Inter-annual context.	Climate-scale trend and long-term AEP robustness [179].	Long hindcasts and reanalyses.

8.1.1. Supervised learning

Supervised learning uses labeled data, with each input characteristic having a known result [188,191]. The goal is to learn a mapping that can be generalized to the test data [188,192]. In wave energy research, supervised learning takes two primary forms: regression and classification [27,182].

Supervised learning based on regression is concerned with predicting continuous variables, such as WEC power output, absorbed

energy, significant wave height, wave period, or optimum power take-off (PTO) parameters [27,188]. Popular algorithms are support vector regression (SVR), random forests, gradient boosting methods, and artificial neural networks [27,182]. These models are generally trained on historical buoy observations, reanalysis, or numerical modeling to predict nonlinear relationships between environmental conditions and energy produced [182,185].

Supervised learning based on classification, on the other hand, predicts a discrete label [193]. In the case of wave energy, classification has been used for sea-state classification, operational mode classification, and reliability or fault state classification of WEC parts [27,182]. Such models convert continuous sensor or environment data into symbolic states that can be used to support maintenance decisions and control logic [27,182].

On the whole, the wave-energy AI research to date is mostly regression-based, mirroring the prevalence of continuous performance prediction tasks, such as power prediction and resource evaluation [27, 182].

8.1.2. Unsupervised learning

Unsupervised learning uses unlabeled data and has the purpose of extracting hidden structure from observations [193]. The main tasks are clustering, dimensionality reduction, and pattern discovery [193, 194]. In the wave energy field, clustering techniques have been applied mainly for grouping sea states, for characterizing wave-wind regimes, and for partitioning the operation conditions of WECs [120]. Methods like k-means, hierarchical clustering, and self-organizing maps allow scientists to condense large datasets into representative classes that can simplify control schemes and analysis of resources [120,195].

Solutions such as principal component analysis and autoencoders are used to compress the high-dimensional environmental inputs while maintaining the dominant patterns of variability [193]. Unsupervised learning methods are not as frequently used as supervised prediction in WEC applications, but they do have an important underpinning function in exploratory data analysis and feature extraction [182].

8.1.3. Reinforcement learning

Reinforcement learning (RL) addresses the challenges of sequential decision-making, wherein an agent engages with the environment, executes actions, and receives rewards or penalties [196,197]. RL differs from supervised learning in that it does not need labeled data sets; its learning is based on cumulative reward maximization over time [193]. This principle is especially suited for the control optimization in wave energy systems [27,182].

The reward function is usually linked to captured power and structural safety, and RL has been studied for adaptive PTO and motion control in the WEC literature [27,183]. Without wave predictions, RL formulations treat the WEC operation as a dynamic process that allows the controllers to adjust to changes in the sea state in real time [189]. For this, algorithms like actor–critic architectures, policy gradient, and Q-learning have been examined [27].

8.1.4. Physics-informed and physics-aware machine learning

Physics-informed machine learning is a hybrid framework that integrates physical knowledge into data-driven models, directly addressing the fundamental weakness of black-box approaches: the absence of physical constraint satisfaction [198,199]. ML models for WEC applications are best understood along a spectrum from fully black-box to fully white-box, with physics integration possible at three levels: the loss function, the input feature space, or the network architecture [198, 200].

Black-box models — including standard LSTM networks, gradient boosting ensembles (XGBoost, LightGBM), and feedforward ANNs — learn input–output mappings entirely from data without embedded physical knowledge [27,182]. They offer maximum flexibility and can achieve high statistical accuracy on in-distribution test sets, but provide no guarantee that predictions respect conservation of energy, satisfy Cummins equation dynamics, or remain within the theoretical CWR bound. In small-dataset regimes typical of Malaysian coastal WEC sites, black-box models are prone to overfitting and may produce physically implausible predictions under extrapolation conditions [25,188].

Gray-box or physics-aware models incorporate physical structure at one of three levels: (1) at the input feature level, by using physically

meaningful variables (H_s , T_p , device resonance frequency ratio) rather than raw sensor signals; (2) at the architecture level, by designing network structures that mirror physical model structures — for example, using a recurrent architecture to emulate the memory kernel of the Cummins radiation force convolution integral; or (3) at the training level, by incorporating BEM-computed hydrodynamic coefficients (added mass, radiation damping) as additional physics-derived input features to an ML surrogate [198,200].

White-box physics-informed neural networks (PINNs) go furthest by embedding the governing equations directly into the loss function as soft constraints during training [199,201]. For a heaving point absorber, the Cummins equation takes the form:

$$(M + A_\infty)\ddot{x}(t) + \int_0^t K(t - \tau)\dot{x}(\tau) d\tau + K_h x(t) = F_{\text{exc}}(t) + F_{\text{PTO}}(t) \quad (2)$$

where M is device mass, A_∞ is infinite-frequency added mass, $K(t)$ is the radiation impulse response function, K_h is hydrostatic stiffness, F_{exc} is wave excitation force, and F_{PTO} is PTO control force [97,128]. A PINN trained to predict WEC motion or power output includes a residual term penalizing violation of this equation during training, ensuring physically consistent predictions even under data-scarce conditions [199]. In wave energy contexts, physics-informed machine learning can impose hydrodynamic limitations, energy conservation principles, or simplified wave theory on neural networks that forecast power output or dynamic response [27,202]. This property is especially valuable for Malaysian applications where long-term measured wave and power data are unavailable — the PINN can be pre-trained on BEM simulation data and fine-tuned on sparse measured records [203].

The choice between black-box, gray-box, and PINN approaches should be guided by dataset availability, required generalization range, and the consequence of physically inconsistent predictions. For operational power forecasting at a well-instrumented site with abundant data, black-box LSTM models may suffice. For design optimization, control synthesis, or deployment at a new Malaysian coastal site with limited data, physics-informed approaches are strongly preferred [198, 203]. This black-box to white-box taxonomy offers a systematic framework for classifying AI/ML methods in wave energy and establishes the conceptual basis for the subsequent model-specific discussions.

8.2. Traditional ML & ensemble models

Conventional ML models used for BWECs are typically shallow, non-temporal algorithms such as Support Vector Regression (SVR), Gaussian Process Regression (GPR), k-nearest neighbors (kNN), Random Forest (RF), Gradient Boosting Machines (GBM), XGBoost, LightGBM, CatBoost, and Multi-Layer Perceptrons (MLP) with few hidden layers [25, 27,155,188,204]. In contrast to deep learning architectures presented in subsequent sections, these models are substantially based on manually crafted features extracted from wave climate indicators and device parameters [25,27]. A representative overview of such studies — spanning WEC farm power prediction, wave energy flux forecasting, capture width ratio estimation, and geometry optimization — is provided in Table 8, which summarizes key model configurations, data sources, and reported performance metrics across eight recent works. In WECs, classic ML techniques are mainly employed for regression problems, such as prediction of instantaneous/average power output, wave energy flux prediction, capture width ratio estimation, and geometry/ballast optimization on biomimetic devices modeled after designs such as the Salter duck [25,152,155,188,204].

One of the main advantages of these models is that they can achieve high predictive performance even when trained on small- to medium-sized datasets and therefore are well-suited for early-stage WEC development where there is a lack of large-scale operational data [25,27,155,188]. Tree-based ensemble methods, especially Random Forest and its gradient boosting extensions (XGBoost and LightGBM), offered better performance than linear regression since they are

able to capture strong nonlinear relationships among significant wave height (Hs), peak period (Tp), wave direction, PTO parameters, and geometric inputs [25,27,155]. As reflected across multiple entries in Table 8, ensemble models have been shown to generate much higher R^2 (> 0.95 – 0.98) on established benchmarks such as the UCI WEC dataset [25,155]. Stacked and hybrid ensembles formed by a number of boosted learners also enhance robustness in multi-site or farm-level power prediction applications [25]. Hybrid decomposition–ML frameworks have also been investigated, where wave energy time series are decomposed by means of methods such as EEMD, and then SVR, RF, or boosting models are applied to each component, achieving better stability and short-term prediction results [27].

While they have benefits such as low computational cost, interpretability, and support for easy design space exploration, conventional ML-based models do depend on feature engineering and hyperparameter tuning [25,27,188]. They usually do not have the inherent ability to model and learn complex spatial–temporal dependencies of wave fields, and their extrapolation performance can be reduced for unseen sea states [25,27]. Hence, as summarized in Table 8, these models serve as important foundational references in the WEC prediction literature, preceding the more expressive deep learning and physics-informed approaches discussed in the subsequent sections [25,27]. Although ensemble models achieve high R^2 on benchmark datasets, they remain black-box and do not inherently enforce Cummins equation dynamics or the theoretical CWR limit; physics-informed extensions are therefore recommended for Malaysian deployment contexts where physical consistency cannot be sacrificed for statistical accuracy.

8.3. Feedforward and spatial deep learning models for WEC prediction

Feedforward and spatial deep learning (DL) models are becoming the key instruments for WEC forecasting, as they are highly suited for capturing complex nonlinear relations between multivariate wave states and WEC responses [27]. Contrary to conventional linear or statistical model-based predictions, these deep architectures are well suited for high-dimensional interactions with multivariate, irregular sea states to conduct real-time predictions with fast computational speed, which support control, digital twins, energy management, etc. A representative selection of such models and their applications is summarized in Table 9, covering a range of architectures from standard feedforward networks to hybrid spatial–temporal models across diverse WEC types and datasets. Among the feedforward models, multilayer perceptrons (MLPs or ANNs) are very popular to represent nonlinear mappings between the input variables (e.g., significant wave height (Hs), peak period (Tp), wind speed, spectral descriptors, and power-take-off parameters) and output variables (e.g., WEC power, excitation forces, and absorbed electrical power) [27]. However, MLPs are constrained by a lack of temporal memory, and thus they are not as suitable for highly nonstationary or broadband wave fields, and they need to be regularized carefully to prevent overfitting when trained on small data sets [208].

Deep neural networks (DNNs) generalize MLPs by using multiple layers, which can hierarchically extract features and represent more complex non-linear hydrological transformations. DNNs are becoming promising surrogates of computationally expensive CFD or high-fidelity simulations to predict multiple outputs simultaneously while maintaining the inter-variable correlations [209]. Low-fidelity linear models with deep networks developed for multi-fidelity methods can be enhanced even more in terms of predictive power and efficiency [209]. Instead, convolutional neural networks (CNNs) take advantage of spatial or spectral correlations by convolving with convolutional filters, which makes processing wave fields, spectral images, or reanalysis grids as a whole feasible without handcrafted features [210]. Hybrid models based on CNN coupled with recurrent structures such as CNN–LSTM, considered herein, are capable of exploiting both spatial and

temporal correlations and exhibit superior multi-location WEC power forecasts [211].

Generative models like GANs allow for wave height predictions at high spatial resolutions, converting wind information or coarser wave data into finer wave field realizations [212]. On the other hand, physics-informed neural networks (PINNs) embed the governing hydrodynamic equations as a constraint in the training of neural networks and enhance the generalizability and trustworthiness in the presence of limited data [203]. In areas where observation records are scarce, like Malaysia, transfer learning provides a viable approach to adapt pretrained models from data-abundant areas, mitigating the issues arising from paucity of data [213]. Overall, as reflected across the studies summarized in Table 9, feedforward and spatial deep learning frameworks are able to deliver accurate, versatile, and computationally efficient methods for WEC prediction and serve as the building blocks for hybrid, physics-coupled, and data-efficient techniques in wave energy prediction [27].

8.4. Time-series deep learning models

Time-series deep learning (DL) models are leading the development of WEC systems, mainly in predicting wave motions and energy conversion [215,216]. These architectures, in particular the Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), naturally fit the complex nonlinear wave energy system [215,217]. Unlike traditional models that rely on shallow feature engineering, deep learning architectures process raw or minimally processed time-series data, allowing them to capture intricate temporal patterns directly from wave and device signals [215,218]. This is especially useful for modeling long-term dependencies, which is a challenge for simpler architectures like standard RNNs [215,217].

LSTMs and GRUs are widely used for time series predictions, e.g., wave elevation and excitation force estimation [216,219]. They are well suited to capture the dynamics of a wave energy system because of their long-range dependence [215,217]. Bidirectional LSTMs (BiLSTMs) and the encoder–decoder framework have been shown to be more promising for multi-step predictions since they leverage future context hence improving the short-term WEC power generation prediction [220,221]. Hybrid models involving CNNs and LSTMs or GRUs (e.g., CNN–BiLSTM–DELA) achieved best performances (R^2 values near 0.99), especially in WEC power generation forecasting in short-term [222]. These hybrids take advantage of CNN's ability to extract local temporal features and the sequential capabilities of LSTMs for long-term dependencies [218]. According to Table 10, Wang et al.'s [156] stacking ensemble of LSTM and LightGBM had the maximum accuracy ($R^2 = 0.9974$, $RMSE = 0.5049 \text{ kW m}^{-1}$) at four NDBC buoy sites. For all JONSWAP circumstances, Zhang et al.'s [223] LSTM model had a R^2 value of more than 0.99. Bhamu et al.'s [224] edRFT model beat all the baselines, with an RMSE of 0.4792 over 15 datasets.

Wavelet transform and empirical mode decomposition (EMD) methods are also integrated in some DL models to deal with high-frequency noise and variability of wave conditions and to improve robustness of models [225]. The decomposition of frequencies enhances the precision of the forecasting, particularly when the signal is noisy or chaotic [225]. The approach is high precision in the prediction of both wave height and wave energy [219,225]. Nevertheless time-series deep learning models also have certain drawbacks. They usually need big data sets to train them, data that might not be easy to find, in particular if one is dealing with the real-world WEC operations [215]. Training these models may have a high computational cost, and hyperparameter tuning is an additional complexity during their deployment [219]. Also, these models are more difficult to generalize to unseen sea states, which decreases their flexibility in real applications [215]. Their lower interpretability compared to classical ML models adds another layer of complexity for their application in real systems [217]. Huang et al.'s [63] review pointed out that no particular prediction

Table 8
Summary of traditional ML and ensemble models for WEC power and wave energy prediction.

No.	Citation	Model used	WEC/ Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
1	Muthamizhan et al. (2025) [25]	Stacking Ensemble: XGBoost + LightGBM + CatBoost (base) + Ridge Regression (meta); Optuna + 10-fold CV	CETO-type 16-unit WEC farm; predict total farm power output at 4 Australian coastal sites	UCI ML Repository; 4 sites (Adelaide, Perth, Sydney, Tasmania); ~72,000 instances/site	16 WEC positions → Euclidean distance features + P1–P16 power; PCA → 20 features	Total power output (W) = sum of P1–P16	MAE, MSE, RMSE, R^2	Best $R^2=0.8897$ (Perth); MAE=6601 W; RMSE=9090 W (Sydney)	Hybrid stacking beats all individual models. XGBoost is best standalone. WEC spatial positioning critically affects output. Tasmania most difficult.
2	Pérez-Molina & Carta (2025) [185]	Six ML compared: MLR, SVR, KNN, RF, XGBoost, ANN; best: MLR $\equiv$ SVR; 10-fold CV + grid search; Wilcoxon test	MCP for long-term wave power estimation at Gran Canaria from ERA5 reference	Buoy 2442, Gran Canaria (780 m); ERA5 (ECMWF); Jan 2000–Dec 2023 (24 years, hourly)	$\ln(H_{e,ERA5})$; $\ln(T_{e,ERA5})$; log-transformed, z-score normalized	P_{wave} kW m $^{-1}$; $0.5 \times H_s^2 \times T_e$	MAE, RMSE, R^2 ; Wilcoxon + Benjamini–Hochberg	MLR: MAE=2.56 kW m $^{-1}$, RMSE=4.49 kW m $^{-1}$, $R^2 \approx 75.5\%$; ERA5 RMSE=7.10 kW m $^{-1}$	ERA5 overestimates by ~40% in winter. MLR preferred for parsimony. One year sufficient for training.
3	Torabbeigi & Abolfathi (2025) [205]	Hybrid ML–Transfer Function; MLP (best), RF, GBRT; Grid Search 5-fold CV; MinMaxScaler	MBFWEC – cylinder + 4 floats; estimate Total Absorbed Power (TAP) via ML–TF hybrid	ANSYS AQWA + WEC-Sim; 2112 wave scenarios; Oman Sea: 3 stations; 209 sea states (2016)	Wave height H (m), frequency f (Hz), PTO damping (MNms/rad)	CWR (%); TAP (kW) via TF $\times$ wave power spectrum	R^2 , RMSE, MAE; max TAP error (%)	MLP: $R^2=0.9955$, RMSE=1.170; TAP error <4%; ~80% cost reduction	MLP outperforms RF and GBRT. Wave frequency most important predictor. Swell states yield higher energy capture.
4	Poguluri & Bae (2024) [188]	MLP, SVR (RBF kernel), XGBoost; GridSearchCV 5-fold; best: XGBoost ($R^2=0.995$)	Salter's Duck – pitch-type; optimize ballast weight + position to maximize power; 25 configurations	WAMIT + CFD Star-CCM+; 2850 data points; 10,000 LHS samples; Jeju Island (1979–2008)	Ballast weight (%) (X_p), Z_p (m), B_{vis} , $\dot{B}_{PTO}$, ω (rad/s)	P_{opt}/a^2 kW m $^{-2}$	RMSE, MAE, R^2	XGBoost: $R^2=0.995$, RMSE=5.758, MAE=1.217; AEP=35.83 MW (Jeju)	XGBoost with tuning vastly outperforms others. Ballast weight and position critically affect performance.
5	Yang et al. (2023) [45]	AutoARIMA, ForecastHybrid; H2O-AutoML (GBM, XGBoost, DNN, SE), Rminer, AutoKeras; best: H2O-AutoML	WEF prediction in Bohai Sea via SWH + MWP; 31 grid points; 2022–2030 forecast	ERA5 monthly reanalysis 1979–2021; 43 years; 31 grid points; $0.5^\circ \times 0.5^\circ$; GEBCO bathymetry	23 temporal features from monthly SWH and MWP; month, week, quarter, day of year	SWH (m), MWP (s); derived WEF kW m $^{-1}$	RMSE, MAPE, CCC, Pearson r	SWH RMSE: 0.07–0.11 m; MWP RMSE: 0.15–0.20 s; Max WEF ~1.5 kW m $^{-1}$	H2O-AutoML dominates all 31 points. Strong seasonal dependency. First AutoML application to WEF.
6	Pasta et al. (2023) [181]	RF: 50 trees, max leaf 10; DNN: 5 hidden layers ($32 \times 4+1$), ReLU+tanh, Adam; with/without 14 extra features	PeWEC – pitching resonant device; data-driven PI reactive control; maximize absorbed power over 1 year	ERA5 – Alghero, NW Sardinia; 2018 wave sequence; Pierson–Moskowitz spectra; year-long simulation	T_e , H_s , θ_1 , θ_2 ; extended: + squared terms + log cross-products	Avg. P_{abs} (kW) per 10-min; EAEP MWh yr $^{-1}$	EAEP vs IM benchmark (~136 MWh yr $^{-1}$)	RF + extra: 158 MWh/yr (+16.2%); DNN + extra: 155 MWh yr $^{-1}$ (+14.8%)	All data-driven configs beat IM controller. RF + extra features achieves fastest convergence and highest EAEP.
7	Pani et al. (2021) [206]	Stacking Regressor: Decision Tree + XGBoost (base); baselines: LR, KNN, DT, XGBoost standalone	Wave energy flux forecasting at Diamond Shoals, NC (Buoy 41025); also predicts H_s and wave period	NOAA NDBC – Buoy 41025; Jan 2014–Dec 2019; hourly; ~52,560 records	Wind gust, wind speed, WVHT, APD, air temperature	WVHT (m), APD (s), wave flux E (kW m $^{-1}$)	RMSE, R^2	Wave flux: RMSE=0.1778, $R^2=0.9203$; Wave height: RMSE=0.2710	XGBoost achieves best RMSE and R^2 . Stacking compensates for individual model weaknesses.
8	Fernández et al. (2015) [207]	Ordinal: SVOREX, SVORIM, KDLOE, ELMOR, ONN, POM; Nominal: SVC1V1, SVC1VA; SVR; Gaussian kernel; nested 5-fold CV	H_s and F_e classification at 6-hour horizon; 2 NOAA buoy sites (Alaska and North Carolina)	NOAA NDBC – Stations 46001 (AK) and 41013 (NC); NCEP/NCAR Reanalysis	4 meteorological variables $\times$ 4 grid points = 16 features: air temp., pressure, u , v winds	Ordinal class of H_s (m) or F_e kW m $^{-1}$ [4–6 classes]	CCR (%), MAE; Friedman + Holm	SVOREX: CCR=65.17% (4 classes, NC); SVORIM MAE=0.359; SVR worst across all datasets	First ordinal classification applied to wave energy. Ordinal SVMs outperform all others. F_e harder to predict than H_s .

approach prevails under all wave conditions, underscoring the necessity of considering wave prediction, excitation force estimates, and control as a cohesive system. Hybrid AI-physics models achieved goodness-of-fit scores of 80%–90% against physics-based MPC baselines, while combining MPC with LSTM-based wave prediction increased power capture by 185% over passive resistive damping in simulated JONSWAP conditions [63]. Critically, this figure derives from numerical simulation on synthetic wave data rather than real ocean deployment; the two studies in Table 11 validated on real ocean records [183,189] report more conservative improvements of 24%–152%, reflecting the additional variability, PTO losses, and stroke constraints present in operational conditions.

Despite these challenges, time-series DL models represent a cutting-edge approach to learning complex, nonlinear temporal dynamics in WECs and show great promise for improving the efficiency and reliability of WEC systems. Overall, the studies in Table 10 indicate

that the field has moved from standalone LSTM and GRU architectures to more advanced ensemble, hybrid, and attention-augmented frameworks. The most recent models consistently achieve R^2 values above 0.99 and RMSE reductions of over 60%–90% compared to traditional statistical baselines — specifically ARMA, Weibull regression, and standalone SWAN numerical models-across wave forecasting and WEC power prediction tasks [182,186]. However, these results are obtained predominantly on single-site measured datasets (NOAA NDBC buoys, ERA5 grid points) or synthetic JONSWAP tank data with 80/20 temporal train/test splits; their transferability to the non-stationary, data-scarce Malaysian coastal environment has not been demonstrated. Integrating these models with physics-informed extensions and uncertainty quantification holds potential for overcoming some of their current limitations and enhancing their practical applicability [215,221]. Standard LSTM and hybrid time-series architectures achieve strong predictive accuracy under stationary training conditions but cannot

Table 9

Summary of feedforward and spatial deep learning models for WEC power and wave energy prediction.

No.	Citation	Model used	WEC/Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
1	Zhang et al. (2025) [22]	OceanCastNet (OCN) – AFNO framework from FourCastNet; 12 AFNO layers; $\mathcal{O}(N \log N)$ via FFT/IFFT; auto-regressive wind-forced; masked loss function	Global DL wave forecasting; alternative to ECWAM physics model; simultaneous H_s , T_m , θ_m prediction globally	ERA5 reanalysis (1980–2020); train 1980–2017; ECWAM operational forecasts (2024); NDBC buoys 56 stations (2020 & 2024); Jason-3 satellite (2024)	12 channels = 3 time steps $\times$ 4 variables: U_{10} , V_{10} , H_s , T_m , θ_m ; past states + current & future wind	H_s (m), T_m (s), θ_m (degrees)	ACC, RMSE, ME, Pearson r	Idealized (360-hr): H_s ACC>0.96, RMSE<0.25 m; NDBC 2020: $r = 0.91$, RMSE=0.47 m; Speedup > 10,000x vs traditional models	OCN matches operational ECWAM accuracy. Auto-regressive wind-forced design critical for extreme events. Consumer GPU sufficient for 10-day global forecast in ~10 s. First DL model with simultaneous global triple-output (H_s , T_m , θ_m).
2	Saavedra et al. (2025) [208]	4 NN architectures: FNN (static), FNN_big (deep static), FNN_pas (past samples), RNN (recurrent); Levenberg–Marquardt; MSE cost; 2 input feature groups	1:20 scale Wavestar-like pitch WEC; estimate wave excitation torque (d , Nm); first evaluation for Wavestar-type WEC; real tank data	SWELL open-access dataset (Faedo et al. 2023); physical wave tank – National Maritime Research Institute, Japan; 5 sea states; 200 Hz; 300 s per sea state	Group 1: θ , $\dot{\theta}$; Group 2: θ , $\dot{\theta}$ + η_s , η_r (wave probes; Spearman r : –0.86, –0.856, –0.819 with target)	Wave excitation torque d (Nm)	MSE, MAE, R^2	Best: FNN_pas (Group 2): $R^2=0.991$ (SS2); MSE=0.133 overall; MSE reduction up to 90.3% vs FNN	Temporal architectures outperform static NNs (up to 90% MSE reduction). FNN_pas beats complex RNN. Adding wave probes improves all models. SS3 (wide-banded) most challenging.
3	Zhang et al. (2024) [21]	Stage 1: BiGRU (power matrix); Stage 2: CNN-BiLSTM-DELA – parallel CNN + BiLSTM with novel DELA attention (Spatial + Channel + Local modules); Adam; Cosine LR	Point absorber WEC with direct-drive PMLG; short-term power output forecasting (South China Sea)	ERA5 (ECMWF) – 116°E, 16.5°N; 1-hr intervals; Jan–Dec 2023 (8593 points); generalization: Jan–Jun 2024	H_s and T_p (Pearson: $r \approx 0.989$ and $r \approx 0.766$); input: 24 time steps (24 h)	WEC power output (W); 1-step-ahead; test horizon: 168 h	MSE, MAPE, MAE, R^2	CNN-BiLSTM-DELA: MSE=0.0396, MAPE=3.74%, $R^2=98.69\%$ (2023); generalization (2024): $R^2=97.12\%$; MSE 62.5% below nearest rival	DELA attention outperforms all 7 alternative mechanisms. Parallel CNN captures extreme wave events. Strong temporal generalization ($R^2=97.12\%$ on 2024 out-of-sample data).
4	Mahmoodi et al. (2022) [214]	NAR Network (Levenberg–Marquardt, Bayesian Regularization, SCG); GMDH (self-organizing); LSTM (250 neurons, Adam); all compared for excitation force forecasting	Two-body heaving point absorber WEC (RM3 – NREL); forecast wave excitation force for WEC power maximization control	WEC-Sim + WAMIT simulations; 6 wave spectra (JONSWAP, PM, Bretschneider); 24,006 total samples; train: 0–390 s; test: 390–400 s	Past wave elevation $\eta(t)$ (m); horizons: 10, 30, 70, 100-step ahead (1–10 s at 0.1 s sampling)	Wave excitation force $F_{ext}(t)$ (MN) on floating body and spar (heave)	MAE, RMSE, R^2 , SI	Best: NAR (LM, 10 neurons); 10-step: NAR $R^2=0.845$, GMDH $R^2=0.771$, LSTM $R^2=0.677$	NAR best for generalization on unseen data. GMDH near-perfect on training but poor generalization. LSTM worst on test (small dataset). All methods degrade at longer horizons.

guarantee physical consistency with wave–structure interaction dynamics; physics-informed extensions that embed governing hydrodynamic equations as training constraints directly address this limitation and are particularly important for Malaysian data-scarce deployment scenarios.

8.5. Reinforcement learning for WEC control

Reinforcement learning (RL) has emerged as a promising approach for controlling WECs, addressing the limitations of traditional model-based strategies [226,227]. Conventional control methods, such as Model Predictive Control (MPC) and shape-based control, often rely on linearized hydrodynamic models that neglect the complex nonlinear dynamics of power take-off (PTO) systems and wave-structure interactions [226,228]. This leads to discrepancies between predicted and actual power output [226]. Unlike these model-based approaches, RL optimizes control policies through direct interaction with the environment, enabling the system to adapt to real-world complexities that are difficult to model explicitly [226,228]. This capability makes RL particularly suited for improving WEC performance from a global, wave-to-wire perspective [187,226].

Before characterizing RL's distinct advantages, it is important to acknowledge that conventional MPC has itself undergone substantial recent improvements that partially address some of its original limitations. Lin et al. [229] performed a comprehensive sensitivity analysis of a complete MPC system incorporating wave excitation force estimation and prediction, revealing that the full estimation–prediction–control

loop exhibits sensitivity behaviors completely different from an isolated MPC controller: under certain model errors in mass and stiffness identification, the complete system can become unstable or enter a “self-locking” state that is entirely invisible when examining the controller in isolation. This study further demonstrated how linear control-oriented modeling can partially address nonlinear viscous and friction dynamics through artificial parameter scheduling, and quantified the inherent accuracy–robustness trade-off in estimator and predictor tuning. In a complementary contribution, Lin et al. [230] developed a high-fidelity PTO loss model encompassing generator copper and iron losses alongside power converter losses, and demonstrated that a quadratic loss approximation embedded within a loss-aware MPC (quad-LAMPC) framework achieves near-optimal electrical power production — over 98% of the high-fidelity optimum — while maintaining the quadratic programming structure required for fast real-time computation. These represent significant engineering advances: quad-LAMPC achieves computation speeds 100 times faster than nonlinear MPC alternatives while preserving near-optimal wave-to-wire efficiency, confirming that MPC remains a highly competitive control paradigm for well-characterized, single-device deployments. Nevertheless, RL offers distinct and complementary advantages in scenarios where MPC's structural assumptions are difficult to satisfy. First, while linear control-oriented modeling can partially capture viscous and friction nonlinearities through parameter scheduling, MPC's performance remains susceptible to mass and stiffness identification errors that can cause instability or self-locking — behaviors that are entirely absent from model-free RL agents that learn

Table 10
Summary of time-series deep learning models for WEC power and wave energy prediction.

No.	Citation	Model used	WEC/Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
1	Huang et al. (2026) [63]	Review: AR, ARMA, KF, EKF, AKF, DMS, LWT, HOS, CWM/ICWM, ANN, BNN, CNN, RNN, LSTM, NAR, GMDH, LWT-LSTM, LWT-PINN; Excitation: WED-EFR, PK-EFR, MOB-EFR; Control: MPC, EMPC, PSC; 138 references	Full pipeline review: Wave Prediction → Excitation Force Estimation → Predictive Control → Robust Control; first review treating all three stages as integrated coupled system	Multiple sources: upstream arrays, single-point sensors, EMEC buoy data, WEC-Sim, WAMIT; phase-averaged and phase-resolved methods	Wave elevation $\eta(t)$; wind speed/direction; wave height/period; system state; PTO force history; upstream wave probe measurements	Wave elevation forecast; excitation force estimate; WEC control force (PTO); power capture/energy yield	GoF (%), energy (kJ), power increase (%), RMSE, ε_p	ICWM: $\varepsilon_p \sim 4.25\%$; Hybrid GoF: 80–90%+; Reactive+AR: 360% power increase; MPC+LSTM: 185%; PSC: 99% optimal at horizon <30 s	No single method dominates all scenarios. Hybrid AI+physics achieves highest GoF. ICWM best physical model at low–moderate steepness. Prediction-based control improves power up to ~80% over classical resonance.
2	Wang et al. (2025) [156]	Stacking ensemble: LSTM + LightGBM (base) + Linear Regression (meta); 5-fold CV stacking; 3-fold CV base tuning; Baselines: CNN, LSTM, LightGBM, partial stacks	Short-term ocean wave power flux forecasting; 4 NDBC buoy stations covering North Atlantic and Gulf of Mexico	NOAA NDBC – Buoy 41025, 44065, 42055, 41002; full year 2016; hourly; ~34,815 samples; 80/20 train/test	Pearson-selected 5 features: H_s , T_d , V_s , ρ_{lagged} ; excluded: mean wave direction	Wave power flux p kW m^{-1} = $0.491 \times H_s^2 \times T_d$; ($T_d = 1.14 \times T_p$)	R^2 , RMSE, MAPE, MSE kW m^{-1} , kW m^{-2}	Buoy 42055: $R^2=0.9996$, RMSE=0.2026 kW m^{-1} ; Avg: $R^2=0.9974$, RMSE=0.5049 kW m^{-1} ; MSE reduction up to 90.18%	Stacking consistently outperforms all single and partial-hybrid models. LSTM outperforms CNN. All 4 sites achieve $R^2 > 0.99$. Meta-learner reduces overfitting.
3	Bhambu et al. (2025) [224]	edRFT: stacked hidden layers as independent regressors; median fusion; skip connections; RVFL random weights + Transformer encoder; Ridge Regression output per layer; Layer-wise Bayesian Optimization (TPE, 100 trials/layer)	Significant wave height forecasting; 5 NDBC buoy stations in Gulf of Alaska; 4-hour ahead forecasting	NOAA NDBC – 5 stations Gulf of Alaska (46001, 46076, 46077, 46080, 46083); 2017–2019; hourly; ~131,400 samples; 70/10/20 train/val/test	WVHT, WSPD, WDIR, GST, APD; optimal lag: 16 steps; Min-Max scaled to $[-1, 1]$	WVHT (m) at 4-hour horizon	RMSE, MASE, MAPE; Friedman + Wilcoxon + Nemenyi tests	Mean RMSE=0.4792, MASE=2.897, MAPE=0.133; Best: Station 46077 (2019) RMSE=0.3368; Testing: 10.09 s vs LSTM 19.4 s	edRFT best average ranks confirmed by Friedman ($p < 10^{-11}$). Randomized training outperforms gradient-based in same architecture. Spring most predictable; Fall most challenging.
4	Varela et al. (2024) [186]	Systematic review of 44 ML models: DL 18 (LSTM, BiLSTM, CNN, GANs, BNN, PatchTST, ICEEMDAN-ELM, Ensemble 13 (RF, XGBoost); Regression 10 (AR, SVR, GWO-GMDH); Hybrid: SWAN+XGBoost, CEM+ML	Review of ML/DL for ocean wave energy forecasting: SWH, wave period, energy flux, WEC power	NOAA NDBC, satellite SAR, WaveHub Cornwall, Coast Lab Plymouth, South China Sea buoys, SWAN/WW3, Lake Erie, China marine stations	H_s , wave period, direction, energy flux, wind speed, atmospheric pressure, SST, seabed topography, SAR images	SWH (H_s), wave energy period (T), wave energy flux (P), WEC control strategy	RMSE, MAE, R^2 , MAPE	ICEEMDAN-ELM RMSE=0.016–0.018 m ($R^2=0.999$); Hybrid EN-1/EN-2 MAPE=2.24–3.71%; GANs spatial RMSE=0.24 m	Hybrid models outperform standalone. LSTM most widely used. DL surpasses WW3/SWAN. Transformers and GANs emerging. Rapid growth post-2020.
5	Zhang et al. (2024) [223]	LSTM (1 hidden layer + FC 128 units); Adam; LR=0.005; 100 epochs; MATLAB; min-max normalized; optimal input = 15 steps	Short-term wave height prediction for non-causal WEC control; UoP COAST Lab wave tank (1:50 scale); 4 JONSWAP cases including 50-year extreme	COAST Lab, Univ. of Plymouth, UK; JONSWAP ($\gamma=3.3$ and 1.0); 4 wave conditions; 128 Hz; 80:20 train/test	Wave surface elevation $\eta(t)$ (m); input lengths 15, 30, 45, 60 steps tested; optimal: 15 steps	Wave surface elevation at next time step; 60-second future prediction	R^2 , RMSE (m), MAE (m)	All 4 cases $R^2 > 0.99$; Best $R^2=0.9990$ (Case #4, 50-year extreme); Best RMSE=0.000573 m (Case #1)	LSTM achieves $R^2 > 0.99$ across all conditions including 50-year extreme. Shorter input (15 steps) outperforms longer. Robust across narrow and broad JONSWAP spectra.
6	Shadmani et al. (2023) [27]	Review: ANN, LSTM, CNN, RNN, DNN, SVM, RF, MLP, GRU; hybrid models (EMD-LSTM, CEEMD-ELM, STL-CNN-PE); supervised, unsupervised, semi-supervised and RL	Wave forecasting (H_s , T_p , direction); WEC power prediction; PTO optimization; real-time WEC control via RL	Buoys (Caspian Sea, Hawaii, Spain, Bay of Biscay, US coastal); NCEP; ECMWF; GDAS; SIMAR; Gulf of Mexico 13 sites; Perth WA; Sri Lanka	Varies by study; mainly H_s , T_p , wave direction, wind speed, atmospheric pressure	Mainly H_s , T_p , WEC power output, WEC control policy	RMSE, MAPE, MAE	Jorge et al. LSTM RMSE=0.069 m; bathymetry improved LSTM by 16.7% RMSE; Gracia MLP+GBDT reduced variance by 36%	ANN most widely used (~72%). CNN and LSTM most promising DL. RL emerging for real-time model-free WEC control. Hybrid physics-ML superior.
7	Clemente et al. (2023) [182]	Review of 60+ post-2016 papers: ANN/MLP, CNN, RNN, LSTM, GRU/BIGRU, DNN, MTEANN, SVM/SVR, RF; Direct: GA, PSO, SOS, ANFIS, AR/ARMA, Bayesian	Wave climate and energy resource assessment: H_s prediction, energy flux, wave propagation, extreme events, climate change impact	NOAA NDBC, ERA5/SIMAR, WAVEYRS, Jason-3/SARAL/HY2B altimeters, SWAN, X-band radar, India ADCP, Taiwan coastal, Delft3D	H_s , T_p , T_s , T_m , wind speed/dir., air pressure, SST, water depth, wave direction, ocean currents, radar images	H_s , T_p , wave energy flux, mean wave period, wave excitation force	RMSE, MAPE, MAE, MASE, SI, R^2 , Pearson r	RF+SWAN: $R^2=0.9067$, RMSE=0.2556 m (~100x faster); James ANN: 4000x faster than SWAN; Fan SWAN-LSTM: 65% more accurate	ANNs dominant in ~72% of studies. AI models 4000x faster than SWAN. Hybrid AI+numerical outperforms standalone. LSTM/GRU preferred for sequential data.
8	Gu & Li (2022) [202]	Review: CNN, RNN, LSTM, GRU, BiGRU/BiLSTM, DBN, DNN, hybrid models (CNN+LSTM, CNN+GRU, LSTM+ELM); 2016–2021 literature	Review: wave height & period prediction, wave energy flux, wind speed/power, wave farm layout, WEC optimization, pattern recognition	NOAA WAVEWATCH III, NOAA NDBC, NREL Wind Integration, LIDAR, Canadian ISDM, Belgian DSO, NOAA altimeter; multiple global locations	Wind speed/dir., H_s , wave period, atmospheric pressure, SST, salinity, precipitation, turbine params, radar images	Wind speed/power, H_s , wave period, wave energy flux, typhoon trajectory, wind farm cluster power	MAE, RMSE, MAPE, R^2 , SI, Pearson r	LSTM $R^2=0.9992$ (wind speed); BiGRU MAE=0.425, RMSE=0.64 (3–24 hr horizon); Hybrid CNN+GRU MAE=0.844	Hybrid models consistently outperform single-architecture models. GRU faster than LSTM with comparable accuracy. Preprocessing (EMD, VMD, wavelet) consistently reduces error.

dynamics through direct environmental interaction [229]; Furthermore, Zhan and Ringwood [227] identified a fundamental 'modeling paradox' inherent to MPC: energy maximization requires large device oscillations, but these large motions invalidate the small-amplitude assumptions underlying the linear models that MPC relies upon — precisely when accurate modeling is most critical. The model-free

linear noncausal optimal control (MF-LNOC) via RL they are proposing does not suffer from such a paradox and can converge within only 150 s of operational data, allowing for real-time reconfiguration as sea states change, which is extremely useful in the monsoon-driven non-stationary weather pattern of Malaysia. Second, quad-LAMP's near-optimal efficiency relies on accurate sea-state information to schedule

quadratic loss coefficients across varying conditions [230]; RL agents, by contrast, adapt to PTO losses dynamically across monsoon-driven sea-state shifts without requiring explicit sea-state estimators or look-up tables. Third, optimization-based MPC faces increasing real-time computational burdens when scaled to multi-body or array-level WEC systems, whereas trained RL controllers — consisting primarily of matrix operations — execute on the order of 10^{-4} seconds [231], and MARL-based array control achieves 94% of centralized MPC efficiency at 99% reduction in computational cost [232]. Finally, non-predictive RL formulations such as CFD-coupled SAC latching control [233] eliminate dependence on wave forecasting entirely, overcoming the performance losses inherent in wave prediction errors that limit MPC's non-causal advantage.

A notable example of RL application in WEC control is Zou et al.'s use of Deep Q-Networks (DQN) for controlling a direct-drive point absorber [183]. The DQN is trained on full electromechanical variables, including float displacement, velocity, and PTO currents, which allows the agent to implicitly learn the optimal PTO loss–power extraction trade-off that traditional controllers miss [183]. When tested with real ocean data from PacWave, the DQN agent demonstrated significant power improvements, ranging from 24% to 152% over conventional model-based control, while remaining operational throughout the year [183]. In contrast, shape-based control failed in seven out of twelve months due to stroke limit violations [183]. At a larger scale, Sarkar et al. applied Proximal Policy Optimization (PPO)-based Multi-Agent Reinforcement Learning (MARL) to the industrial CETO 6 platform, using LSTM-based policy networks [187]. Their approach, which incorporated a 10-second wave look-ahead, not only optimized power extraction but also minimized structural yaw stress to just 2%–4% of baseline values, achieving power gains across a broad wave period range (6–16 s) [187]. This approach outperformed other RL methods such as DQN and A3C in terms of training stability [187].

Soft Actor–Critic (SAC) and Deep Deterministic Policy Gradient (DDPG) techniques, which have demonstrated efficacy in intricate fluid–structure interaction environments [228], are further developments in RL for WEC control. When combined with high-fidelity Computational Fluid Dynamics (CFD) models, SAC in particular has demonstrated exceptional stability and sample efficiency and has increased energy harvesting in oscillating wave surge converters by 10.61% [228]. Ye et al. [234] proposed a high-fidelity SPH-based simulation framework combined with SAC-based DRL to enhance adaptive PTO damping in the presence of time-varying waves, this work extends the CFD-coupled DRL methodology to OWSCs in particular. They achieved 10.61% energy improvement in 2D environments and 22.54% in 3D environments. Critically, policies trained in computationally efficient 2D environments demonstrated robust transferability to complex 3D wave-structure interactions including slamming and overtopping phenomena — nonlinear effects that conventional linear MPC models cannot accurately represent.

Recent research has significantly expanded the scope of reinforcement learning for wave energy converter control across four essential dimensions: nonlinear hydrodynamics, safety constraint enforcement, array-level scalability, and experimental validation, with comprehensive comparisons of model configurations, datasets, and performance metrics presented in Table 11. Qin et al. [233] integrated CFD with SAC-based DRL for non-predictive latching control, effectively addressing nonlinear viscous effects unattainable by potential-flow-based reinforcement learning environments, and attaining conversion efficiency over 30% without necessitating wave prediction. To address the inherent constraint-enforcement gap in standard reinforcement learning (RL), Chen et al. [231] introduced a shield-enhanced safe RL (SE-SRL) framework that iteratively predicts potential violations and adjusts control actions prior to execution, ensuring stringent safety bounds — a capability that soft-penalty RL cannot consistently deliver — while operating in approximately 10^{-4} seconds for real-time applicability. Chen et al. [232] verified a Multi-Agent Reinforcement Learning (MARL)

framework utilizing Centralized Training and Decentralized Execution (CTDE) through wave tank testing, attaining 94% of centralized Model Predictive Control (MPC) efficiency at a 99% reduction in computing cost. Pierart et al. [235] presented one of the initial experimental applications of reinforcement learning on a physical wave energy converter, achieving an 11.3% enhancement in energy efficiency via Q-learning in the presence of actual irregular waves, while also affirming that unaccounted friction and nonlinearities pose significant obstacles for practical implementation. Ultimately, at the electromechanical level, Qin et al. [236] amalgamated DQN with a Field-Weakening Optimization (FWO) mechanism to explicitly address nonlinear PMLG voltage and current constraints, thereby augmenting the generator's operational speed range by 10% and enhancing power capture by 70% compared to MPC.

Notwithstanding these gains, reinforcement learning for wave energy converter control encounters several hurdles. Training is computationally demanding, frequently necessitating hours or days of GPU-based processing [187]. Although recent research has initiated the bridging of the simulation-to-deployment gap via physical tank experiments [232,235], most reinforcement learning models continue to be validated solely through numerical simulations, with scant evidence from open-sea deployments [226]. A further problem involves managing limitations on float displacement and PTO forces, which are challenging to apply consistently in continuous reinforcement learning formulations [183]. Although shield-enhanced and FWO-constrained methodologies signify significant advancements in this domain [231, 236], the emphasis has predominantly been on traditional point absorbers and the CETO 6 multi-generator apparatus, with insufficient investigation into the application of RL techniques to biomimetic and other multi-body WECs, as well as to varied wave climates, thereby highlighting a critical research deficiency [187,237].

In summary, RL has demonstrated substantial potential for improving WEC control, particularly in overcoming the limitations of traditional methods [226,228]. However, challenges related to computational cost, constraint handling, and real-world validation need to be addressed for its wider adoption in operational settings [232]. The Malaysian wave climate is strongly influenced by the northeast and southwest monsoons, producing pronounced seasonal shifts in significant wave height and energetic sea states in the South China Sea region, with higher waves during the northeast monsoon and relatively calmer seas in other periods. The comparative advantages of RL over MPC are particularly pronounced under such non-stationary conditions: while quad-LAMPC requires accurate sea-state scheduling of its quadratic loss coefficients [230], and complete MPC systems remain susceptible to instability under model identification errors [229], RL agents can adapt dynamically to monsoon-driven sea-state shifts without relying on precise system identification or explicit wave prediction. The shield-enhanced safe RL framework [231] further addresses hard constraint enforcement — a critical property for surviving abrupt extreme monsoon wave events that soft-penalty RL cannot reliably handle. These considerations collectively suggest that RL, particularly with safe constraint mechanisms and MARL array coordination, represents the most operationally viable intelligent control paradigm for future BWEC deployments in Malaysian nearshore waters. Under such non-stationary conditions, conventional soft penalty reward terms in continuous RL may be insufficient to prevent stroke and PTO force violations during abrupt extreme events. Future RL formulations could adopt constrained optimization frameworks (e.g., CMDP with hard constraint enforcement via Lagrangian/primal–dual schemes) to ensure safety bounds are respected, and multi-objective reward structures that balance power capture with survivability by penalizing large excursions of displacement and force, scaling with real-time sea state severity [187]. Additionally, incorporating structural loading proxies in the reward could further mitigate fatigue risk in biomimetic devices.

Table 11
Summary of reinforcement learning and model predictive control methods for WEC control and optimization.

No.	Citation	Model used	WEC/Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
1	Teixeira-Duarte et al. (2025) [26]	Multi-Objective Genetic Algorithm (GA); K-Means clustering for sea state reduction; SNL-SWAN spectral wave model for fitness evaluation; WECs as linear obstacles with frequency-dependent transmission coefficients	WaveRoller® B-OF OWSC (26 m wide, 3.332 MW/device); farm of 150 WECs (500 MW) at Esposende, Portugal; dual objectives: maximize wave energy capture (q -factor) and coastal protection (HRA)	SNL-SWAN model; wave data from Clemente et al. (2025); bathymetry from Instituto Hidrográfico; 8 representative sea states via K-means; JONSWAP spectra; 3.75×3.6 km domain	H_s , T_p , mean wave direction θ_m ; bathymetry (3×3 m resolution); JONSWAP parameters; GA: population 200, crossover 70%, mutation 1%, elite size 3	q -factor (array vs isolated WEC power); HRA% (wave height reduction area); WLA Index (normalized composite metric)	q -factor, HRA (%), power (MW), CoV, P2M, MAPE	Scenario 1: $q=0.79$ – 0.80 , HRA $\approx$ 19%, power $\approx$ 48.9 MW; +25.9% q -factor and +39.6% HRA vs fixed benchmark; Fixed benchmark: $q=0.64$, HRA=13.4%, power=38.8 MW	GA-optimized layouts consistently outperform fixed benchmark in both objectives. Rapid improvement in first 30–40 GA generations. Coastal protection layout clusters WECs near shoreline. Framework is model-agnostic.
2	Wang et al. (2024) [189]	Double Deep Q-Network (DDQN) + TVPD control; 2 NNs (Q-network θ and target θ^-); 2 FC layers $\times$ 24 neurons; SGD; prediction horizons $N=1, 3, 5$ tested; optimal: $N=3$	Single point absorber WEC with hydraulic PTO (seabed-fixed); non-causal WEC control incorporating wave predictions directly into model-free RL	Real wave data from Cornwall/Wales, UK; computer-generated irregular waves (robustness test); Nvidia GTX1650 + Intel i7-9750H; training: ~ 6 – 12 h	Device state: displacement z_o , velocity $\dot{z}_o$; wave prediction vector $\mathbf{w}_{pre} = [w_1, \dots, w_N]$ (N -step ahead elevation; optimal $N=3$)	Time-varying PD gains $K_p(n)$ and $K_d(n)$ updated every 0.5 s; PTO force: $F_{PTO} = K_p(n) \cdot s_n + K_d(n) \cdot \dot{\mathbf{w}}_{pre}$	Energy output (kJ) over 200 s	DDQN Horizon-3: 102.0 kJ; 3.69x traditional PD (27.64 kJ); Horizon-5: 100.9 kJ with fewer training episodes (21 vs 73); Robust: $<0.1\%$ variation at SNR=0 dB	DDQN non-causal control significantly outperforms traditional PD. Horizon-3 best energy; Horizon-5 best training efficiency. Robust to prediction errors and model uncertainties. Applicable to soft-body WECs.
3	Umeda et al. (2024) [184]	Gaussian Process Regression (GPR) – nonparametric Bayesian surrogate; polynomial kernel; 2 separate GPRs (displacement & velocity); optimize PI reactive control (K_v , K_p) via GPR simulation	1:20 scale point-absorber WEC (heave-only; 0.40 m float); commercial PMLG PTO; Type-1 data-driven control; no analytical WEC model required	Physical wave tank – National Maritime Research Institute of Japan (50 m $\times$ 8 m $\times$ 4.5 m); JONSWAP $\gamma=1.0$; $H_s=0.1$ m; $T_s=1.23$ – 2.12 s; training: only 3 wave conditions	Float position $x(t)$, velocity $\dot{x}(t)$ (preceding 2.0 s); PTO force $f_{pto}(t)$ (preceding 2.0 s); wave elevation $\zeta(t)$ (± 2.0 s total 4.0 s)	Float displacement $x(t + \Delta t)$ and velocity $\dot{x}(t + \Delta t)$ one-step-ahead; maximize average net power P_{net}	Average net power (W); constraint satisfaction (position ≤ 0.15 m, force ≤ 140 N)	GPC1 matched ACL across all tested wave periods; generalized to $T_s=1.46$ s and 2.12 s not in training; GPC2 (20 N force): constraint satisfied	First experimental validation of GPR-based WEC control under real tank conditions. Matches optimal reactive control without system identification. Generalizes to unseen wave conditions trained on only 3 conditions.
4	Wang, Z. (2023) [64]	Model Predictive Control (MPC) with Quadratic Programming; nominal model (linear, no viscous forces) vs real model (with mismatch + prediction errors); penalty weights $r=2 \times 10^{-11}$, $q=3 \times 10^{-7}$	Point absorption WEC with hydraulic PTO (float mass 242 kg, restoring 3866 N/m, $u_{max}=1.5$ kN); analyze effect of prediction steps, model mismatch, wave prediction errors, and constraints	No external dataset; JONSWAP synthetic waves ($H_s=1.5$ m, $T_p=12.56$ s); 200-second simulation; numerical only	Wave surface height Z_w ; velocity $\dot{Z}_w$; system state (z_o , $\dot{z}_o$); predicted future wave excitation force; prediction steps $N=5$ – 12 tested	Control force u (PTO force); total energy captured (kJ) over 200 s	Total energy (kJ); average power (W)	Optimal $N=10$ (~ 1050 W avg); Nominal MPC: 193.7 kJ; Real model (mismatch): 146.9 kJ (-24.18%); Real + tight constraint (0.5 m): 133.4 kJ (-31.16%)	Optimal prediction step $N=10$. Model mismatch reduces energy by 24.18%. Nominal simulations significantly overestimate real-world performance. Tighter constraints further reduce energy capture.
5	Zou et al. (2022) [183]	Deep Q-Network (DQN) + TVPD control; 2 DNNs (target θ^- and Q-network); 2 hidden layers $\times$ 24 neurons; ReLU; Adam; 1200 episodes; $\gamma=0.999$; $\delta_{RL}=0.1$ s	Small-scale direct-drive point absorber WEC (radius 0.5 m, mass 399.15 kg); Linear Electrical Machine (LEM) PTO; maximize wave-to-wire electricity	Simulated wave-to-wire MATLAB; Bretschneider waves ($H_s=1$ m, $T_p=8$ s) for training; real PacWave (Pacific NW, USA) 12-month H_s and T_e for validation	Displacement (z), velocity ($\dot{z}$), LEM d -axis current (i_d), q -axis current (i_q) [full mechanical and electrical state]	Time-varying PD gains $K_p(t)$ and $K_d(t)$ updated every 0.1 s $\rightarrow$ PTO force reference to maximize instantaneous electrical power	Avg power improvement (%), PTA ratio, COV	DQN avg power improvement: 24%–152% over model-based; SB achieves only $\sim 80.4\%$ of DQN; SB fails (NaN) in 7/12 months; DQN functional all 12 months	DQN outperforms model-based controls across all 12 months. Optimizes from global wave-to-wire perspective including PTO losses. Model-based controls fail by ignoring PTO losses. Lowest COV among all tested controls.
6	Sarkar et al. (2022) [187]	Multi-Agent RL (MARL) using PPO; 2-agent and 3-agent tested; LSTM-based policy and critic networks; cooperative–competitive reward with team coeff η ; PPO selected after comparing DQN, SAC, A3C	CETO 6 (Carnegie Clean Energy) – 3-legged submerged buoyant actuator; 3 independent PTOs; 6 DoF; multi-objective: maximize energy, minimize yaw stress, survivability under 7 m waves	CETO 6 simulator; JONSWAP spectrum; wave data from Albany (W. Australia), Arminza (Spain – BiMEP), Wave Hub (Cornwall, UK); wave periods 6–16 s; ~ 50 M steps; 1–3 days on 8xNVIDIA V100	Buoy position/vel./accel. (6 DoF), rotational yaw, tether extension/velocity, wave elevation and rate of change (present + 10 s ahead from upstream sensors)	Reactive force commands for each PTO generator per leg; controlling generator resistance to maximize power and minimize yaw stress	Energy capture gain over Spring Damper (%), yaw reduction (%)	PPO-MARL avg gain: 19.9% over SD (frontal); 13.9% (30° angled); yaw reduced to 2.6% of SD (normal 2 m); 3.5% (extreme 7 m); PPO beats SAC (3.2%) and A3C (14.8%)	3-agent MARL with PPO achieves double-digit energy gains over full wave frequency spectrum (6–16 s). Near-eliminates yaw stress ($\sim 2\%$ – 3% of baseline). LSTM policy with 10-s look-ahead enables long-horizon decisions.

(continued on next page)

Table 11 (continued).

No.	Citation	Model used	WEC/Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
7	Qin et al. (2025) [233]	SAC-based DRL (non-predictive latching agent); CFD–DRL coupling; parallel training in 3 state-space configurations; no explicit parameter tuning required	Heaving point absorber; latching control in unpredicted irregular wave environments; CFD numerical wave flume (NWF) as training environment	2D NWF built by solving incompressible Navier–Stokes equations; irregular waves via Pierson–Moskowitz spectrum; captures nonlinear two-way WEC–wave coupling and vortex shedding	WEC displacement, velocity; wave height observation points from CFD state space; 3 state-space configurations tested	Binary latching/de-latching decision at each time step	Wave energy conversion efficiency (%); stability vs. traditional latching control	Conversion efficiency >30%; DRL latching superior in both efficiency and stability to traditional threshold-based latching; generalization across multiple irregular wave environments	First CFD-coupled DRL latching controller for irregular waves. CFD environment captures nonlinear viscous effects that potential-flow RL environments overestimate. Parallel training enhances generalization. Number of wave observation points and retraining frequency are critical performance factors. Non-predictive design eliminates dependence on wave forecasting.
8	Chen et al. (2025) [231]	Shield-Enhanced Safe RL (SE-sRL); WEC state prediction network for multi-step constraint forecasting; shield mechanism refines actions before execution; shared-layer design; two-stage training; data augmentation	Nonlinear WEC; model-free safe PTO control enforcing displacement and force constraints while maximizing power	Simulation-based; nonlinear WEC model with physical constraints	WEC state (displacement, velocity, PTO force); recursively predicted future states for constraint checking	Shield-adjusted PTO control force; constraint satisfaction status	Energy capture vs. unconstrained RL (%); constraint violation rate; execution time (s)	Higher energy capture than soft-penalty RL; zero reliable constraint violations; execution time $\sim 10^{-4}$ s (real-time feasible)	Shield mechanism performs multi-step constraint lookahead, preventing structural damage during training and deployment. Overcomes fundamental limitation of soft-penalty RL where penalty terms distort the control objective. Shared-layer design and data augmentation improve sample efficiency. Execution speed confirms suitability for high-frequency embedded WEC control hardware.
9	Qin et al. (2025) [236]	DQN + Field-Weakening Optimization (FWO); DQN optimizes damping and stiffness; FWO handles nonlinear PMLG voltage/current constraints; two-stage control: RL outer loop + FWO inner constraint enforcement	Direct-driven WEC with PMLG PTO; maximize wave-to-wire electrical power while satisfying nonlinear generator electrical constraints	Numerical simulation + experimental validation; multiple sea conditions	Float displacement, velocity; PMLG d -axis and q -axis currents; voltage state; sea state parameters	PTO damping and stiffness coefficients; field-weakening control signal	Power capture improvement vs. resistive control (%); improvement vs. MPC (%); operational speed range extension (%)	37%–65% power improvement over resistive control; 70% improvement over MPC; operational speed range extended by 10%	First RL framework to explicitly integrate PMLG electrical machine constraints (nonlinear voltage/current limits) into the WEC control loop. FWO extends generator operational envelope beyond conventional linear constraints. Substantially outperforms MPC by capturing full wave-to-wire losses rather than treating PTO as an ideal actuator. Directly relevant to linear generator PTO systems favored in Malaysian nearshore deployments.

(continued on next page)

Table 11 (continued).

No.	Citation	Model used	WEC/Application	Data source	Input features	Output variable	Metrics	Best result	Key findings
10	Ye et al. (2025) [234]	SAC-based DRL; SPH-CFD coupling via SPHinXsys; comparative analysis of PPO, TD3, SAC; 2D→3D policy transfer	OWSC adaptive PTO damping optimization; nonlinear wave-structure interactions including slamming and overtopping	SPH-based numerical wave tank (SPHinXsys + Simbody); regular and irregular wave conditions; 2D and 3D environments	OWSC displacement, velocity; wave elevation; PTO damping state	Optimal adaptive PTO damping coefficient; energy harvesting efficiency	Energy improvement % over constant damping baseline	SAC: 10.61% improvement (2D); 22.54% improvement (3D); 2D-trained policies robust and transferable to 3D	SAC outperforms PPO and TD3 in capturing nonlinear OWSC hydrodynamics. 2D-to-3D policy transfer validated. Single-agent damping control insufficient for dual OWSC arrays due to strong nonlinear harmonics — motivating MARL.
11	Chen et al. (2026) [232]	MARL with MATD3 algorithm; three architectures compared: CTCE, DTDE, CTDE; control-oriented loss model embedded in reward; force penalty to avoid high-loss PTO regions; physically validated in wave tank	Point-absorber WEC arrays with PMLG PTO; maximize electrical power generation while managing inter-device hydrodynamic interactions and PTO losses	Physical wave tank experiments + numerical simulation; irregular wave conditions	Per-device float displacement, velocity; PTO force; neighboring device states (CTDE)	Per-device PTO damping force reference; electrical power output	Array energy efficiency vs. centralized MPC (%); computational cost reduction (%); constraint satisfaction	CTDE achieves ~94% of centralized MPC energy efficiency; 99% computational cost reduction vs. centralized MPC; tank tests confirm simulation-to-experiment transferability	CTDE is optimal architecture balancing efficiency and scalability for WEC arrays. Control-oriented loss model in reward prevents operation in high-loss PTO regions. Physical tank validation bridges simulation-to-deployment gap. 99% computational cost reduction makes MARL-CTDE practically viable for large WEC farms where centralized MPC is computationally infeasible.
12	Pierart et al. (2024) [235]	Q-learning (tabular); PTO resistive damping coefficient as discrete action space; convergence in ~40 training episodes; real-time online optimization	Single-body point absorber WEC with resistive PTO; experimental implementation at FloWave Ocean Energy Research Facility, University of Edinburgh, under real irregular wave conditions	Physical wave tank (FloWave, Univ. of Edinburgh); real irregular waves; ANSYS AQWA 2024R1 for hydrodynamic coefficient derivation	Sea state classification; current PTO damping setting; measured power output feedback	Optimal PTO resistive damping coefficient updated in real time	Energy output improvement from initial to optimized state (%); episode convergence count; theoretical vs. experimental agreement	11.3% experimental energy improvement; 12% theoretical improvement; convergence at ~40 episodes; close alignment between theoretical and experimental results	One of the first experimental RL implementations on a physical WEC under real irregular waves. Q-learning converges to optimal PTO damping in real time without requiring a system model. Discrepancies between theoretical and experimental results (from unmodeled friction and nonlinear dynamics) highlight key challenges for real-world RL deployment. Confirms RL's practical feasibility for on-site PTO optimization.
13	Zhan & Ringwood (2024) [227]	MF-LNOC: model-free RL with prefixed linear actor and quadratic critic; control-theoretic RL structure; augmented state with future wave excitation	Point absorber WEC; noncausal energy-maximizing control on continuous action space	Numerical simulation; benchmarked point absorber model; standard WEC parameters	WEC displacement, velocity; augmented future wave excitation prediction	Continuous optimal PTO control force; noncausal control policy	Convergence speed (seconds); power capture vs. best-tuned causal feedback controller	Convergence in under 150 s of data; outperforms best-tuned causal MPC; robust against wave forecasting inaccuracies	Identifies fundamental “modeling paradox” in MPC: large oscillations needed for energy maximization invalidate small-amplitude linear model assumptions. MF-LNOC avoids this by being fully model-free while achieving noncausal optimal performance with minimal data.

8.6. Quantitative meta-analysis of predictive performance

This part consolidates the documented performance of diverse AI/ML categories from earlier sub-sections into a systematic meta-analysis to identify cross-category patterns, benchmark shortcomings, and validation inconsistencies in the wave energy ML literature. Table 12 consolidates critical performance indicators — R^2 , RMSE

range, dataset characteristics, validation methodologies, and overfitting mitigation — from all reviewed papers, enabling a direct quantitative comparison that individual subsection analyses cannot provide.

Several patterns emerge from the meta-analysis in Table 12. First, time-series deep learning models (LSTM, GRU, and hybrid variants) consistently achieve the highest R^2 of 0.9974 across reviewed studies,

Table 12
Meta-analysis of AI/ML predictive performance across reviewed studies Tables 8–11.

AI/ML category	No. of studies reviewed	R^2 range	RMSE range	Typical dataset size & type	Most common validation method	Studies with explicit overfitting mitigation (%)
Traditional ML & Ensemble Models	8 (Table 8)	0.75–0.9955	Variable by output unit; MAE = 1.2–6601 W depending on scale	2112–72,000 samples; mix of simulated (AQWA, WEC-Sim) and measured (NOAA NDBC, ERA5) data	k -fold cross-validation (5- or 10-fold); 80/20 train/test split	6/8 studies (75%); cross-validation, regularization (Ridge), hyperparameter tuning (Optuna, GridSearch)
Feedforward & Spatial Deep Learning	4 (Table 9)	0.845–0.9987	0.133–0.47 m (wave height); varies by output	300 s–41 years; mix of physical wave tank (SWELL dataset), ERA5 global reanalysis, and NOAA NDBC buoy records	Hold-out test set; temporal train/test split; out-of-sample generalization testing	3/4 studies (75%); Bayesian regularization, masked loss function, dropout
Time-Series Deep Learning (LSTM, GRU, Transformer)	8 (Table 10)	0.677–0.9996	0.2026–0.5049 kW m^{-1} (power flux); 0.016–0.479 m (wave height)	8593–131,400 samples; predominantly measured ocean data (NOAA NDBC, ERA5, COAST Lab wave tank); mostly single-site	80/20 temporal split; 5-fold cross-validation stacking; out-of-year generalization (2023 train → 2024 test)	5/8 studies (63%); meta-learner in stacking, Bayesian layer-wise optimization, cosine learning rate decay
Reinforcement Learning & MPC	6 (Table 11)	Not applicable (control output, not regression)	Not applicable; performance reported as % power improvement over baseline	Simulated wave environments (JONSWAP, Bretschneider); 1 study uses real PacWave ocean data; 1 study uses real Cornwall/Wales buoy data	Simulation-based evaluation; 1 study validated on 12-month real ocean data [172]	4/6 studies (67%); target network stabilization (DQN), experience replay, PPO clipping, early stopping
Physics-Informed ML (PINN, GPR, hybrid)	3 (Tables 9–11)	0.845–0.9955; limited sample	0.133–1.170 (force/power units vary)	Very small (3–6 wave conditions from physical tank); physics constraints compensate for data scarcity	Leave-one-out generalization to unseen wave conditions; experimental tank validation	3/3 studies (100%); physics residual loss inherently regularizes; Bayesian kernel (GPR)

but this figure is predominantly based on single-site, in-distribution test sets using stationary spectra — conditions that do not reflect the non-stationary, monsoon-modulated wave climate of Malaysian coastal waters. Second, overfitting mitigation is explicitly reported in only 63%–75% of studies across all ML categories, meaning that a substantial minority of reported accuracy figures may reflect training-set memorization rather than genuine generalization capability. Third, reinforcement learning studies are almost entirely validated through simulation rather than real ocean deployment, with only two of six reviewed studies testing on measured ocean data — a significant gap for operational credibility. Fourth, physics-informed approaches, despite being represented by only three studies in this review, achieve competitive accuracy with the smallest datasets (as few as three wave conditions), supporting their suitability for data-scarce Malaysian deployment contexts. Fifth, no study in Tables 8–11 was trained or validated on Malaysian coastal wave or WEC operational data, confirming the critical localization gap identified throughout this review.

9. Conclusion and future directions

9.1. Summary of key findings

This article has reviewed the BWEC design, the wave energy resource in Malaysian coastal areas, and the predictive modeling technique based on AI/ML, in line with 2010–2026 of relevant documents, from 231 peer-reviewed articles that were indexed in Scopus, Web of Science, and IEEE Xplore.

Malaysia possesses a technically viable but low-amplitude, highly seasonal wave climate, with significant wave heights of 0.5–2.0 m and peak periods of 4–8 s, strongly modulated by the northeast and southwest monsoons. Offshore South China Sea power densities reach 50–500 kW m^{-1} , while nearshore zones along the east coast of Peninsular Malaysia, Terengganu, Sarawak, and Sabah record 10–40 kW m^{-1} , confirming the viability of nearshore WEC deployment for island and coastal communities currently dependent on imported fossil fuels.

BWEC designs — including oscillating surge converters inspired by the Oyster, undulating fin mechanisms inspired by rays, and flexible body designs inspired by jellyfish — offer meaningful structural compliance, broadband frequency response, and adaptive hydrodynamic behavior that make them inherently better suited to Malaysian monsoonal sea conditions than conventional rigid WECs designed for energetic North Atlantic swells.

Across AI/ML modeling categories, the literature confirms a consistent progression in predictive accuracy. Traditional ensemble models, including XGBoost and stacking ensembles, achieve $R^2 > 0.95$ –0.98,

establishing strong performance baselines. Time-series architectures, particularly LSTM and GRU variants and their attention-augmented hybrids, represent the current state of practice, with leading studies reporting $R^2 > 0.99$ on single-site benchmark datasets — including NOAA NDBC buoy records (~34,815 hourly samples, 80/20 split [156]) and COAST Lab physical wave tank data (JONSWAP spectra, 80:20 split [223]) — under stationary, in-distribution conditions that do not reflect Malaysian monsoonal non-stationarity. Reinforcement learning combined with MPC and LSTM-based wave prediction has demonstrated power output improvements of up to 185% over passive resistive damping in simulated JONSWAP conditions [63]; real-ocean validated RL studies report improvements of 24%–152% [183], reflecting the additional constraints of operational deployment. PINNs offer a promising but underutilized pathway for physically consistent prediction under data-scarce conditions, particularly relevant for Malaysia where no locally validated AI/ML model currently exists.

9.2. Research gaps

There are well-identified gaps that would severely hinder realization of data-driven, BWEC optimization in Malaysia and similar low-energy, shallow coastal environments despite the documented progress.

- **BWEC device diversity remains narrow.** Existing research is predominantly concentrated on flap-type and oscillating surge configurations, with limited exploration of the broader biological design space. Emerging bio-inspired concepts, including ray-inspired undulating fin converters, jellyfish-inspired pulsatile membrane devices, fish-inspired oscillating foil systems, and soft-body compliant structures, remain at conceptual or early experimental stages, with very few progressing to prototype validation or performance benchmarking.
- **No BWEC has been designed or validated for Malaysian coastal conditions.** Virtually all BWEC studies target high-energy North Atlantic or Pacific environments with significant wave heights exceeding 2–3 m. Direct application to Malaysian nearshore conditions — where H_s ranges from 0.5 to 2.0 m with strong monsoonal seasonality — is technically inappropriate without dedicated redesign and re-optimization.
- **Wave resource knowledge and device deployment readiness remain disconnected for Malaysia.** Existing Malaysian wave energy studies focus predominantly on resource characterization and site identification. No reviewed study has coupled Malaysian wave resource data with BWEC hydrodynamic models to assess device-specific power capture performance under realistic local sea states.

- **Malaysia-specific validated AI/ML predictive models are absent.** No reviewed study has trained and validated an AI/ML model using measured wave and power output data from WEC deployments in Malaysian waters. State-of-the-art models are trained on the North Atlantic or UCI WEC benchmark datasets, for which transferability to the low-amplitude, seasonally varying conditions in Malaysia has yet to be demonstrated.
- **Transformer-based architectures remain underexplored in WEC-specific forecasting.** Although advanced variants such as Informer, Autoformer, PatchTST, and iTransformer have proven superior in long-sequence time-series forecasting in neighboring renewable energy domains, their adoption in WEC prediction remains limited. Key barriers include quadratic self-attention complexity ($O(L^2)$) leading to high computational cost, positional encoding schemes that struggle with non-stationary monsoonal regimes, and the data-hungry nature of Transformers given the scarcity of long-term operational WEC datasets in Malaysian waters. Our bibliometric search returned zero results for “WEC AND transformer AND forecasting” across Scopus, Web of Science, and IEEE Xplore, underscoring this gap.
- **Physics-informed neural networks are severely underrepresented.** Only 29 combined results were identified across all three databases for PINN-based WEC prediction. Given Malaysia’s limited long-term wave measurement infrastructure, PINNs — which embed physical conservation laws directly into the learning process — are particularly well-suited to local data-scarce conditions yet remain largely unapplied.
- **Uncertainty quantification is systematically neglected.** Probabilistic methodologies such as Bayesian neural networks, Monte Carlo dropout, and conformal prediction are scarcely applied to WEC power predictions, even though those are of paramount importance for grid integration planning and financial risk analysis in variable monsoonal wave climates.
- **Transfer learning from high-energy to low-energy wave environments remains unexplored.** There are no studies on domain adaptation or fine-tuning approaches to adapt a high-performing model trained on energetic wave data to the low-amplitude, monsoon-influenced conditions along the Malaysian coastline.
- **AI/ML-based fault detection for BWECS is absent.** Predictive maintenance frameworks specific to BWECS components — including flexible structural elements, bio-inspired PTO mechanisms, and compliant mooring systems — have not been addressed in the reviewed literature despite being a critical requirement for commercial deployment in remote coastal locations.
- **Malaysia-specific dataset collection and AI/ML model development.** Instrumented pilot deployments along Malaysian coastlines are urgently needed. Collaboration between universities, PETRONAS, Tenaga Nasional Berhad, and SEDA Malaysia is recommended to generate locally measured training data for validated predictive models.
- **Transformer architectures for WEC forecasting.** Advanced Transformer variants — including Informer, Autoformer, PatchTST, and iTransformer — should be rigorously benchmarked against LSTM and GRU baselines under non-stationary monsoonal wave conditions.
- **Physics-informed neural networks for data-scarce conditions.** PINN frameworks that encapsulate Morison formulations, oscillating body dynamics, and fluid–structure interaction should be formulated for deployment in Malaysian scenarios where long-term data is not currently available.
- **Probabilistic forecasting and uncertainty quantification.** Bayesian deep learning, conformal prediction intervals, and ensemble-based uncertainty estimation should be incorporated into WEC prediction frameworks to support island microgrid integration planning.
- **Transfer learning for low-energy wave environments.** Domain adversarial training and physics-constrained fine-tuning strategies should be investigated to adapt high-performing models to Malaysian low-amplitude coastal conditions.
- **Fault detection and condition monitoring.** Autoencoder-based anomaly detection, LSTM-based predictive maintenance, and graph neural network approaches should be developed for BWECS component health monitoring in remote coastal deployments.
- **Biomimetic-AI co-design optimization.** Reinforcement learning and Bayesian optimization may be incorporated at the level of BWECS geometry and material design, allowing devices to be co-optimized for the Malaysian hydrodynamic environment and islanded microgrid constraints.

9.3. Future research directions

Based on the gaps identified, the following research directions are suggested to contribute to data-driven BWECS optimization in Malaysia and similar low-energy coastlines:

- **Diverse BWECS concepts.** Prospective research should address bio-inspired archetypes that are still in their infancy — such as manta ray-inspired undulating fin propulsion devices, jellyfish-inspired pulsatile membrane devices, and flexible-body compliant structures — moving from conceptual design through hydrodynamic simulation and scaled prototype testing.
- **Malaysia-optimized BWECS design.** BWECS configurations should be developed and validated specifically for low-amplitude, shallow-water, monsoon-modulated Malaysian nearshore conditions rather than adapted from North Atlantic benchmarks.
- **Coupling wave resource data with hydrodynamic models.** The existing datasets on Malaysian wave resources need to be combined with numerical models of BWECS to evaluate device-specific annual energy output, capacity factors, and optimal deployment locations.

9.4. Conclusion

This review addressed a void in the literature where there was no comprehensive coverage of the BWECS design, Malaysian wave energy resource, and AI/ML-based predictive modeling. Nearshore waves in Malaysia have low amplitude, are highly seasonal, and are influenced by monsoon-induced variability; thus, purpose-developed WEC concepts and locally validated models are required rather than direct implementation of solutions developed in high-energy environments.

BWECS, by virtue of their structural compliance and adaptive hydrodynamic behavior, are well-suited to Malaysian coastal conditions. Together with sophisticated AI/ML frameworks — including ensemble models, deep learning, time-series architectures, reinforcement learning, and physics-informed methods — they provide a compelling route for sustainable coastal electrification.

The bibliometric analysis indicated that LSTM-based architecture dominates the wave energy prediction literature, transformer-based approaches are emergent and unexplored in the area despite their strength in related forecasting application domains, and physics-informed approaches are notably underrepresented. These results outline a promising research direction: comprehensive investigation of Transformer and PINN models for WEC prediction, construction of Malaysia-validated datasets, and integration of probabilistic and co-design optimization schemes. The synergy of bio-inspired design, cutting-edge machine learning, and the energy demands of Malaysia’s coast gives a unique platform for advancing sustainable energy solutions in Southeast Asia and similar low-energy, coastal conditions globally.

CRediT authorship contribution statement

Nuzhat Rahman: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Madiyah Binti Omar:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Nursyarizal B.M. Nor:** Writing – review & editing, Supervision. **Kishore Bingi:** Writing – review & editing, Supervision. **Rosdiazli Ibrahim:** Writing – review & editing, Supervision.

Declaration of competing interest

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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Data availability

This is a systematic review of previously published studies. No new data were generated or obtained during the current study.

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