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A review of artificial intelligence methodologies in marine renewable energy technologies

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ABSTRACT

Artificial intelligence (AI) is increasingly applied to marine renewable energy, but reported performance gains remain difficult to compare because studies differ in task, data regime, baseline, metric, and validation setting. This review synthesizes AI research published between 2010 and 2025 across wave energy, tidal energy, offshore wind, and ocean thermal energy conversion (OTEC). Using a structured coding template, we compare studies by engineering task, model family, decision role, data provenance, comparator, evaluation metric, validation context, and deployment implication. A five-level evidence ladder distinguishes numerical, laboratory, short-campaign, pilot-scale, and long-duration operational evidence. The synthesis shows that AI readiness is strongly domain-dependent. Offshore wind has the most mature evidence, particularly in operational forecasting and O&M, owing to SCADA, condition-monitoring, inspection, alarm, and maintenance data. Wave and tidal applications show promise in short-horizon forecasting, constrained control, and surrogate-assisted design, but remain largely site-specific and validation-limited. OTEC is the least mature domain, with evidence concentrated in component-level prediction, supervisory support, and experimentally bounded optimization. Emerging physics-informed, graph-based, generative, and foundation-model approaches broaden the toolkit, but their engineering value remains validation-dependent. The review contributes an evidence-weighted framework for assessing algorithmic promise, constrained proof of concept, and engineering readiness.

1. Introduction

The transition to low-carbon energy systems is being shaped simultaneously by decarbonization imperatives and concerns over security, resilience, and supply affordability (Chen et al., 2024c; Choudhary et al., 2020). Within that context, marine renewable energy has moved from a peripheral option to a strategically relevant component of the broader energy portfolio (Pan et al., 2021). Wave, tidal, offshore wind, and ocean thermal energy conversion (OTEC) draw on distinct physical resources, operate under different engineering constraints, and occupy different positions on the path from pilot deployment to commercial scale (Almoghayer et al., 2024; Chen et al., 2024b; Rawat and Kumar, 2024; Song et al., 2023). Offshore wind has already achieved substantial industrial deployment in several regions, whereas wave, tidal, and OTEC continue to evolve through demonstration, pilot, and early commercial pathways (Payenda et al., 2024; Rashid et al., 2024b). Collectively, however, these technologies are attractive because they can diversify renewable generation, exploit resource-rich maritime environments, and, in some settings, reduce dependence on imported fossil fuels in islanded and coastal systems (Almoghayer et al., 2024; Choudhary et al., 2020).

Yet marine renewable energy remains difficult engineering. Wave systems must operate under nonlinear hydrodynamics, irregular sea states, and extreme loading conditions (Giorgi et al., 2016; Katsidoniotaki et al., 2025). Tidal technologies face cyclic fatigue, biofouling, array-interaction effects, and demanding site-specific hydrodynamics (Fituri et al., 2020; Habbouche et al., 2024; Qian et al., 2022; Rashid et al., 2024b). Offshore wind, despite its relative maturity, remains constrained by weather-limited access, corrosion, fatigue accumulation, wake interactions, and high operations and maintenance

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costs (Li et al., 2016; Mwangi et al., 2024; Santos et al., 2022; Shafiee et al., 2016). OTEC faces a different challenge set, dominated by narrow thermal gradients, large seawater throughput requirements, and capital-intensive offshore infrastructure (Rashid et al., 2024b; Rawat and Kumar, 2024; Zhu et al., 2024). Across all four domains, technical performance, lifecycle cost, environmental acceptability, and operational reliability are inseparable (Alcibar et al., 2025; Freeman et al., 2021). As a result, progress depends not only on better devices, but also on better forecasting, control, design optimization, monitoring, and maintenance decision support.

Artificial intelligence (AI) has therefore attracted growing interest in marine renewable engineering (Zhao et al., 2024b). However, AI should not be treated as a single solution or as an automatic marker of technological progress (Zhao et al., 2024a). Its value depends on whether a method is matched to the engineering task, the data regime, the governing physics, and the required decision horizon. In some settings, data-driven forecasting can improve short-horizon prediction beyond simple baselines; in others, learning-based control, surrogate-assisted optimization, anomaly detection, or hybrid physics–AI approaches may offer practical gains (Kisvari et al., 2021; Umeda et al., 2024; Yang et al., 2023). At the same time, the evidence base remains uneven (Alcibar et al., 2025; Badoe et al., 2022; Chen et al., 2024a). Many reported gains are derived from simulations, laboratory studies, or short campaign datasets, whereas deployment-oriented confidence requires operationally relevant validation (Alcibar et al., 2025; Badoe et al., 2022; Chen et al., 2024c). For marine renewable energy, the central question is therefore not whether AI has been applied, but where, under what evidence conditions, and with what degree of decision relevance it has demonstrated credible engineering value.

This review addresses that question through an evidence-based comparative synthesis across four marine renewable domains: wave energy, tidal energy, offshore wind, and OTEC. Unlike prior reviews that typically concentrate on individual sectors or method families, this review compares AI evidence across multiple marine renewable domains (Masoumi, 2023; Nakib et al., 2025; Rashid et al., 2023; Shadmani et al., 2023; Zhou, 2022). The contribution of the paper is not broad coverage alone. Rather, it lies in comparing studies across domains using a shared analytical template that captures the dimensions that matter for engineering judgment: the task being addressed, the data regime, representative inputs, the output target, the baseline or comparator, the evaluation metrics, and the maturity of validation. This structure makes it possible to assess not merely which models have been used, but which classes of AI methods are persuasive for particular offshore problems, which results remain conditional on narrow validation settings, and where cross-domain transfer of methodological insight is realistically defensible.

Accordingly, the review is organized around task families that recur across marine energy systems: forecasting, control, design and optimization, and operations and maintenance (O&M). This decision-oriented framing is deliberate. A forecasting model trained on simulated data, a reinforcement-learning controller tested only in a numerical tank, and an anomaly detector evaluated on operational SCADA records do not represent equivalent levels of evidence, even when each reports strong headline performance. By comparing studies through the same task-and-evidence lens, the review distinguishes between algorithmic promise, constrained proof of concept, and deployment-relevant maturity. That distinction is especially important in a field where offshore wind already benefits from comparatively rich operational datasets, while wave, tidal, and OTEC often remain more data-constrained and validation-limited (Chen et al., 2024c; Díaz and Soares, 2020; Kisvari et al., 2021; Li et al., 2024b; Xia et al., 2020).

A further contribution of the review is to make validation maturity explicit in the interpretation of the literature. Near the end of the paper's methodological framing, studies are read through an evidence ladder that differentiates numerical or synthetic validation, laboratory or basin validation, component or short-campaign evidence, pilot or single-site operational evidence, and broader long-duration operational evidence. The purpose of introducing this logic is not to duplicate the methods section here, but to signal the review's interpretive stance: performance claims are weighted by the strength and realism of their validation context. This prevents false equivalence between studies that use different data sources, different comparators, and fundamentally different levels of operational realism.

On that basis, the review develops a comparative account of where AI is currently most mature, where it remains promising but conditional, and where it is still best understood as an emerging research direction rather than an established engineering capability. Offshore wind presently provides the strongest deployment-oriented evidence, particularly in data-rich forecasting and O&M settings (Bashir et al., 2022; Díaz and Soares, 2020; Kisvari et al., 2021; Medina-Manuel et al., 2024; Zhang and Zhao, 2023). Wave and tidal energy show more selective but meaningful progress in forecasting, constrained control, and surrogate-assisted design (Du et al., 2024; Fituri et al., 2020; Qian et al., 2022; Rodriguez-Delgado and Bergillos, 2021). OTEC remains the least mature AI domain, with the literature concentrated mainly on component- or cycle-level prediction and optimization under sparse experimental evidence (Liu et al., 2024a; Rawat and Kumar, 2024; Xia et al., 2020). This uneven maturity is not a weakness to be obscured; it is one of the review's central findings and one of the main reasons a comparative, evidence-weighted synthesis is needed.

The remainder of the paper is organized as follows. Section 2 provides background on the four marine renewable domains and the principal AI families relevant to them. Section 3 defines the review scope, evidence framework, and study-coding logic. Section 4 presents the domain-level review of the literature, organized by engineering task. Section 5 synthesizes the major post-2020 methodological shifts in AI for marine renewable energy. Section 6 develops the cross-domain comparison and synthesis. Section 7 discusses the principal challenges and limitations that continue to constrain reliable deployment of AI in marine settings. Section 8 outlines future research directions. Section 9 concludes the paper.

2. Background and theoretical framework

2.1. Marine renewable energy domains

2.1.1. Wave energy

Ocean waves transport mechanical energy via surface oscillations that, in principle, can be harvested (Sacie et al., 2022). Devices known as wave energy converters (WECs) aim to convert this motion into shaft work and subsequently electricity (Freeman et al., 2021; Ramos-Marin and Guedes Soares, 2025). The resource is undeniably energy-dense, although its practical yield depends strongly on site conditions, spectral characteristics, and survivability constraints (Wang et al., 2023b). Several device archetypes remain under active development—point absorbers, oscillating water columns, attenuators, and overtopping systems—each arguably better suited to particular wave climates and water depths (Neary et al., 2020; Rodriguez-Delgado and Bergillos, 2021). The appeal of wave power often rests on short-horizon predictability and proximity to coastal demand (kumar et al., 2017). Yet familiar problems recur in sea trials: storm loading threatens structural integrity; controllers must cope with broad-banded sea states rather than a single resonant frequency; and offshore deployment and maintenance costs remain high (Freeman et al., 2021; Zadeh et al., 2024). As a result, most projects remain at demonstration scale, with only a few grid-connected units providing sustained data. That paucity of long-duration records limits confident generalization, but it also highlights a tractable opportunity: data-centric design and control (Habbouche et al., 2024). Integrating hydrodynamics, power-take-off modeling, and learning-based controllers could enhance capture width and reduce downtime over time, provided that results are validated beyond tank tests (Bisinotto et al., 2024; Lin et al., 2024b; Stavropoulou et al., 2025). For the AI literature reviewed below, this means that wave-energy results should be read less as evidence of a uniformly mature application area and more as a split evidence base: forecasting benefits from longer environmental records, whereas control, design, and O&M remain constrained by tank, simulation, and sparse offshore failure data.

2.1.2. Tidal energy

Tidal energy offers two pathways to electricity: exploiting the vertical head between high and low water with barrages or lagoons and extracting kinetic energy from swift currents with tidal stream turbines (Bradbury and Conley, 2021; Dokur et al., 2024; Yin et al., 2024). Grid planners often view tides favorably because astronomical forcing yields semi-diurnal or diurnal cycles that are predictable years in advance (Kotta et al., 2020). Predictability, however, is not a substitute for easy engineering. Dense seawater imposes high thrust and torque, reversing flows create cyclical fatigue, and wetted surfaces invite biofouling that degrades performance (Habbouche et al., 2024; Rashid et al., 2024b). Permitting can be lengthy where devices share space with sensitive estuaries or fisheries.

Commercial deployments remain sparse. La Rance in France, operating since 1966, is the canonical reference, whereas many recent efforts focus on stream turbines at pilot scale (Rashid et al., 2024b; Schmider et al., 2024). The hydrodynamics are complex: blockage effects, array-scale wake interactions, and site-specific turbulence all matter (Fituri et al., 2020; Qian et al., 2022). These features make tidal energy a selective rather than generic AI opportunity: AI is most defensible where local turbulence, stratification, meteorological forcing, or array interactions reduce the adequacy of harmonic and physics-based baselines, but claimed improvements require corroboration beyond short campaigns and site-specific numerical studies.

2.1.3. Offshore wind energy

Offshore wind farms deploy turbines in marine or large-lake environments to harness stronger, steadier winds (Mwangi et al., 2024). Over roughly two decades, the technology has moved from niche demonstrations to a mainstream option, with individual turbine ratings now exceeding 15 MW and large farms operating in Europe, parts of Asia, and North America (Payenda et al., 2024). Compared with many onshore sites, offshore locations tend to have higher mean wind speeds, lower turbulence, and fewer land-use conflicts (Anwar et al., 2017; Pan et al., 2021). Fixed-bottom foundations dominate in shallow water, while floating offshore wind turbines (FOWTs) target depths greater than about 50 m (Li et al., 2024d). Díaz et al. (2022) examine the emerging floating offshore wind sector, finding that while floating turbines enable wind development in deep waters, the technology is still costly and faces significant market and technical barriers that must be overcome for broader commercial rollout.

Challenges remain material and logistical. Weather windows and vessel availability constrain installation and servicing at sea, and operations and maintenance can account for roughly a quarter to a third of lifetime costs (Santos et al., 2022; Shafiee et al., 2016). Corrosion, seabed scour, and fatigue loading across towers, blades, and moorings require careful aero-hydro-servo-elastic design and continuous monitoring (Ahmad et al., 2023). A countervailing strength is data abundance. Utility-scale farms generate extensive SCADA records, structural health monitoring signals, and environmental measurements (Díaz and Soares, 2020; Kisvari et al., 2021).

These datasets support a growing body of machine-learning work on performance assessment, fault prediction, wake-aware control, and design feedback for the next generation of machines, although concerns about data access and model transparency continue to surface in industry discussions (Janssens et al., 2016; Quevedo-Reina et al., 2025; Yao et al., 2025).

2.1.4. Ocean thermal energy conversion (OTEC)

OTEC attempts to turn the small temperature gradient between warm surface waters and cold deep waters in the tropics into electric power. In a typical closed-cycle configuration, warm water around 20–26°C vaporizes a working fluid such as ammonia, the vapor drives a turbine, and cold water near 4–5°C condenses it back to liquid (García-Gómez et al., 2023; Lou et al., 2024). The narrow temperature span limits the theoretical efficiency to under about 7–8 percent for a 20°C gradient, and practical plants often achieve on the order of 3–4 percent once pumping and other parasitic loads are included (Baek et al., 2023). The hydraulics are demanding: a 1 MW plant may require approximately 4 m^3/s of warm water and 2 m^3/s of cold water to be supplied continuously (Rashid et al., 2024a). That scale implies large heat exchangers, high-capacity pumps, and a deep cold-water pipe extending more than a kilometer, with clear implications for capital cost and reliability (Rashid et al., 2024a). Under stable conditions, it can provide round-the-clock output and be configured to co-produce desalinated water or district cooling. Most deployments remain at pilot scale in locations such as Hawaii and Japan (Stamoulis et al., 2018; Xing et al., 2023). Given the multi-physics nature of the system—thermodynamics, fluid mechanics, marine engineering—and the limited operating history, AI and advanced modeling could assist with cycle optimization, supervisory control under changing ocean conditions, and component-level forecasting of issues such as biofouling or heat-exchanger degradation (Kondeti and Palanisamy, 2025; Rawat and Kumar, 2024). Whether these tools translate into measurable performance gains will likely depend on sustained field evidence rather than simulation alone.

2.2. Artificial intelligence in ocean renewable energies

2.2.1. AI techniques in renewable energy systems

A technically coherent review of artificial intelligence (AI) in marine renewable energy requires a taxonomy that distinguishes three analytical levels: how a system learns, what model family represents the mapping, and how model outputs are converted into engineering decisions (Donti and Kolter, 2021). These levels are often compressed into undifferentiated lists of "AI methods," where support vector machines, reinforcement learning, model predictive control, and genetic algorithms appear as comparable categories. In this review, they are separated into a three-layer hierarchy—learning setting, model family, and decision/control/optimization layer—so that each study can be interpreted in terms of its learning signal, representational structure, engineering task, and evidence base.

The first layer is the learning setting, which refers to the form of supervision or feedback available during training. Supervised learning applies when labeled targets are available, such as wave-height prediction, turbine-power estimation, fault classification, or regression of thermodynamic states in ocean thermal energy conversion (OTEC) (Bao et al., 2024; Halicki et al., 2025; Pan et al., 2021). Unsupervised learning supports clustering, anomaly detection, latent-state discovery, and structure extraction where labels are limited or uncertain (Kong et al., 2026; Mwangi et al., 2024; Sinha and Steel, 2015; Yan et al., 2025). Self-supervised learning is increasingly relevant in post-2020 settings because large volumes of SCADA streams, sensor records, inspection images, and maintenance logs are only partially labeled; representation learning can therefore precede task-specific fine-tuning (Díaz and Soares, 2020; Li et al., 2024e; Su et al., 2024; Zhi and Shen, 2024). Reinforcement learning (RL) is distinct because it learns through sequential interaction, reward, and policy improvement rather than fixed input–output labels (Tang et al., 2024a). This distinction matters because forecasting, diagnosis, and anomaly detection are not the same learning problem as adaptive wave-energy control, wake-aware coordination in offshore wind, or sequential operating policies under tidal variability (Ahmad et al., 2023; Anderlini et al., 2016; Freeman et al., 2021; Rashid et al., 2024b; Zhu et al., 2024). RL is therefore treated both as a learning paradigm and, when coupled to a control objective, as part of the decision layer.

The second layer is the model family or representational class. This layer specifies the function class or inductive bias used to model relationships in data or physics-constrained systems. Kernel and Gaussian-process-style models remain useful for modest-data regression, uncertainty-aware surrogates, and design-space approximation (Baek et al., 2023; Kang et al., 2020; Lokare et al., 2023; Sacie et al., 2022; Sarkar et al., 2016). Tree-based and boosting models are common in tabular monitoring and fault-detection settings (Bao et al., 2024; Sacie et al., 2022). Neural networks, including multilayer perceptrons, convolutional architectures, recurrent networks, LSTM/GRU models, and Transformers, are central to high-dimensional temporal, spatial, and multimodal data (Chen et al., 2024c; Halicki et al., 2025; Li et al., 2024e; Song et al., 2024; Zhang et al., 2022). Post-2020 developments must be made explicit within this layer. Graph learning is relevant to wake-coupled farms, tidal or wave arrays, and sensor networks because these systems are relational rather than collections of independent devices (Manjur et al., 2025; Pierrot and Pinson, 2025). Neural operators are important when the task is to approximate families of parameterized physical responses, such as wake fields or repeated many-query surrogate evaluations (Zhang et al., 2025c, 2025e). Physics-informed and hybrid models integrate learned representations with governing constraints, conservation structure, numerical models, or physical priors, which is particularly important where field data are sparse, extrapolation is unavoidable, and purely black-box interpolation is not sufficient for engineering credibility (Ayyad et al., 2025; Zhao et al., 2024d). Generative models are increasingly relevant for data augmentation, rare-event modeling, missing-data reconstruction, imbalance-sensitive fault detection, and image-rich inspection workflows (Wang et al., 2023a, 2025b; Yin et al., 2024; Zhang et al., 2025c). Large language models and vision-language models are best understood as emerging multimodal foundation-model families whose current role is concentrated in maintenance-log interpretation, inspection support, image-assisted diagnosis, and human-in-the-loop O&M decision assistance rather than autonomous offshore control (Malyi et al., 2026; Nardelli et al., 2022).

The third layer is the decision, control, and optimization layer. This layer describes how predictions, surrogates, or learned policies are converted into engineering action. It includes model predictive control (MPC), RL-based control and related sequential decision frameworks, Bayesian optimization, evolutionary and swarm algorithms, multi-objective optimization, scheduling, and decision-support tools (Ahmad et al., 2023; Bempedelis et al., 2024; Freeman et al., 2021; Liu et al., 2025a; Sarkar et al., 2016; Tang et al., 2024a; Wang et al., 2024). These mechanisms should not be placed on the same plane as SVMs, CNNs, graph models, or neural operators. A model family describes how a relationship is represented; a decision or optimization framework describes how information is used to choose actions under objectives, constraints, uncertainty, and operational trade-offs. In practice, the layers are coupled: a Gaussian-process surrogate may support Bayesian optimization for device or layout design; a neural surrogate may be embedded in MPC for constrained wave-energy control; a graph model may provide wake-aware forecasts for offshore-wind scheduling; and an RL policy may directly define a sequential control strategy (Badhurshah and Samad, 2015; Sarkar et al., 2016; Zhao et al., 2024b; Zhu et al., 2024).

This hierarchy clarifies why SVM, RL, MPC, and GA/PSO should not be presented as peers. SVM is a kernel-based model family that is usually trained in a supervised setting (Kang et al., 2020; Lokare et al., 2023; Sacie et al., 2022). RL is a learning setting and becomes a control strategy only when the learned policy is used for sequential decision-making (Anderlini et al., 2016; Freeman et al., 2021; Tang et al., 2024a). MPC is a control framework that can use first-principles models, learned surrogates, or hybrid predictors (Badhurshah and Samad, 2015; Li et al., 2024c; Zou et al., 2022). GA, PSO, DE, and related algorithms are optimization strategies for exploring design or control parameter spaces; they do not by themselves represent the learned mapping (Liu et al., 2020; Sarkar et al., 2016; Saveca et al., 2023; Sun et al., 2019; Wu et al., 2024). Separating these levels prevents conceptual ambiguity and makes it possible to compare studies according to the problem-data-model-metric-evidence chain rather than by method name alone.

Several important concepts are treated as enabling, deployment, or integration layers rather than as core taxonomic categories. Explainable AI, uncertainty calibration, transfer learning, federated learning, edge deployment, Internet-of-Things connectivity, digital twins, human-in-the-loop supervision, and data-governance architectures affect how models are interpreted, adapted, distributed, connected to infrastructure, or deployed in operation (Dokur et al., 2025; Rajaoarisoa et al., 2025; Zhang et al., 2023a). They can be combined with multiple learning settings and model families: transfer learning may support CNNs or Transformers; XAI may be applied to tree ensembles, graph models, or deep networks; digital twins may incorporate physics-based solvers, neural surrogates, or hybrid estimators; and edge deployment concerns latency, communication, and computational constraints (Rajaoarisoa et al., 2025). Keeping these concepts outside the core hierarchy improves conceptual precision while preserving their importance for operational readiness.

For marine renewable energy, the value of this taxonomy is that studies can be described in a technically precise and decision-relevant way. A study may involve supervised graph learning for offshore-wind power prediction, self-supervised Transformer-based representation learning on multivariate SCADA streams, Gaussian-process surrogates within Bayesian optimization for wave-device design, physics-informed surrogate learning for sparse-data offshore system identification, RL-based control under constrained tidal or wave operating conditions, or LLM/VLM-assisted interpretation of maintenance logs and inspection imagery under human supervision (Ayyad et al., 2025; Baek et al., 2023; Díaz and Soares, 2020; Kisvari et al., 2021; Sarkar et al., 2016; Zhao et al., 2024a; Zhou et al., 2025). The taxonomy also explains why different domains favor different method combinations: offshore wind is more conducive to data-rich O&M analytics, graph learning, and operational forecasting; wave and tidal systems frequently rely on surrogate-assisted optimization and constrained control because field evidence remains thinner; and OTEC is better suited to compact predictors, hybrid thermodynamic models, and supervisory decision support than to broad claims of autonomous intelligence (Bashir et al., 2022; Díaz and Soares, 2020; Kisvari et al., 2021; Zhang et al., 2025d).

In the remainder of this review, “learning setting” refers to how training feedback is obtained, including supervised, unsupervised, self-supervised, and reinforcement learning. “Model family” or “representational family” refers to the function class or architecture used to represent the mapping, such as SVM/kernel models, Gaussian-process-style models, tree-based models, MLP/ANN, CNN, RNN/LSTM/GRU, Transformers, graph neural networks, neural operators, physics-informed or hybrid models, generative models, and LLM/VLM foundation models.

“Decision, control, or optimization framework” refers to how model outputs or learned policies are converted into engineering action, including MPC, RL-based control, Bayesian optimization, evolutionary or swarm optimization, multi-objective optimization, scheduling, and maintenance decision support. Enabling or deployment concepts such as XAI, uncertainty quantification, IoT, edge computing, digital twins, federated learning, transfer learning, data governance, and human-in-the-loop supervision are not treated as model families; they are discussed as integration, validation, or deployment layers.

Overall, this three-layer taxonomy, summarized in Table 1, provides the conceptual basis for the review. It avoids catalog-like enumeration of algorithm names and links AI techniques to engineering tasks, data regimes, and validation maturity. This is essential because the same nominal “AI method” can carry very different evidentiary weight depending on whether it is used for short-horizon forecasting, design-

Table 1
Hierarchical AI taxonomy adopted for marine renewable energy applications.

Layer	Analytical question	What it contains	Representative items	What it should not be confused with
Learning setting	How is the model trained or informed?	The form of supervision or feedback available during learning	Supervised learning; self-supervised learning; unsupervised learning; reinforcement learning	Model family or decision/control/optimization framework
Model family/ representational class	What function class or inductive bias represents the mapping?	The predictive or representational model class used to model relationships in data or physics-constrained settings	Kernel and Gaussian-process-style models (e.g., SVM, GPR); trees and boosting; neural networks (MLP, CNN, RNN, LSTM, Transformer); graph learning; neural operators; generative models; physics-informed and hybrid models	Learning setting or decision/control/ optimization framework
Decision/control/ optimization layer	How are predictions or policies converted into engineering action?	The framework used for control, design search, scheduling, or decision support	Model predictive control (MPC); RL-based control and related sequential decision frameworks; Bayesian optimization; evolutionary/swarm/multi-objective optimization (GA, PSO, DE, NSGA-II); scheduling and decision-support tools	Base predictive model or representational model class

space exploration, fault diagnosis, O&M prioritization, or operational control.

2.2.2. Chronological AI models in renewable energy systems

This section synthesizes the temporal evolution of AI model families, data maturity, and validation practices across marine renewable energy domains. Rather than cataloguing model-level details, it highlights recurring cross-domain shifts in how AI methods are evaluated and interpreted. Across domains, three recurrent trajectories emerge. First, early studies largely relied on soft-computing and classical machine-learning pipelines (e.g., ANN/ANFIS, SVM, tree ensembles) using engineered features and relatively constrained, site-specific datasets. Second, as sensing and monitoring expanded, hybrid workflows became more prominent, combining signal decomposition, surrogate modeling, and learning-based controllers, which improved predictive and control performance but raised questions about portability across sites and operating regimes. Third, recent work increasingly adopts deep-learning and spatiotemporal architectures (e.g., LSTM/Transformer families and graph-based models), accompanied by a growing movement toward hybrid/physics-informed learning and stronger attention to uncertainty quantification and explainability (UQ/XAI) in safety- and cost-critical decisions.

In parallel, evaluation practices gradually shift from single split reporting toward more robust validation (e.g., cross-site tests, stress scenarios, and operationally meaningful metrics). Table 2 summarizes these cross-domain patterns. The chronological pattern should therefore not be read as a simple replacement of older methods by newer ones. Its engineering significance is that model complexity has increased faster than validation maturity in several marine-energy domains; consequently, recent methods only strengthen deployment claims when they are accompanied by stronger baselines, cross-site tests, uncertainty treatment, or operationally realistic validation.

3. Review scope, evidence framework, and study coding

3.1. Review scope and literature boundaries

This review covers the period 2010–2025 and examines artificial-intelligence and machine-learning applications in four marine renewable energy domains: wave energy, tidal energy, offshore wind, and ocean thermal energy conversion (OTEC). The scope includes studies addressing forecasting, control, design and optimization, monitoring, maintenance, reliability, and closely related decision-support tasks. The objective is not to compile an exhaustive algorithm inventory, but to assess how AI is being used across recurring offshore engineering problems and with what degree of evidentiary maturity.

The review gives priority to peer-reviewed journal literature as its principal evidentiary base (Snyder, 2019). Conference papers are retained only when they are technically influential, when they mark a meaningful methodological transition, or when they provide early visibility into a direction that later becomes substantively important. Preprints are used selectively and are interpreted as emerging-direction evidence rather than as the basis for strong maturity claims. This distinction is particularly important in rapidly evolving topics such as graph-based offshore modeling, operator learning, and LLM/VLM-enabled operations and maintenance, where methodological novelty can appear before validation practices stabilize.

The review is explicitly engineering-task-oriented. Across the four domains, AI is interpreted in relation to the problems it is asked to solve rather than by method name alone (Freeman et al., 2021; Kisvari et al., 2021; Sarkar et al., 2016; Zhao et al., 2024a, 2024e). This framing is necessary because superficially similar model labels may correspond to very different evidentiary settings. A short-horizon forecaster trained on buoy archives, a controller tested in a numerical tank, a wake surrogate trained on solver output, and an anomaly detector evaluated on operational SCADA logs do not support equivalent conclusions, even when

Table 2
Cross-domain chronological synthesis of Artificial Intelligence.

Phase	Dominant model family/decision-framework pattern	Data maturity shift	Validation shift
Early stream	**Model/representational family:** ANN/ANFIS/FIS; SVM/kernel models; RF/GB tree-based models. **Decision/optimization framework:** GA/PSO for design or control-parameter tuning.	Limited, site-specific datasets; engineered features; short monitoring windows	Predominantly simulation/lab studies; point-estimate accuracy emphasis
Mid transition	**Model/representational family:** hybrid decomposition + ML predictors; surrogate models. **Decision/control/optimization framework:** optimization-coupled workflows; early RL-based control.	Richer time-series + met-ocean covariates; higher sampling and longer horizons	Mix of simulation + partial field evidence; broader task-specific metrics
Recent expansion	**Model/representational family:** LSTM/GRU/Transformer; spatiotemporal models; graph-learning models. **Enabling/data-integration workflow:** multi-sensor fusion.	Multi-source spatiotemporal data; larger-scale monitoring; higher dimensionality	More operational validation; robustness checks; deployment-relevant metrics
Emerging frontier	**Model/representational family:** PINNs; physics-informed/hybrid models; ML–numerical coupling. **Decision/control/optimization framework:** decision-centric RL-based control; optimization workflows. **Enabling/ deployment layer:** UQ/XAI; digital-twin workflows.	Data + numerical models/digital-twin workflows; explicit uncertainty needs	Cross-site/shift-aware validation; stress testing; reliability/cost trade-off evaluation

each reports favorable numerical performance (Lin et al., 2024b; Raj and Prakash, 2024; Sareen et al., 2023). The methodological framework adopted here is therefore designed to compare studies on the basis of task, data regime, baseline strength, validation maturity, and deployment relevance.

3.2. Study-coding framework

To ensure consistent cross-domain comparison, each study or study cluster is coded using a fixed analytical template. The extracted fields are: engineering problem, data regime and data provenance, representative inputs, learning setting where relevant, model/representational family, decision/control/optimization framework where applicable, output target, baseline or comparator, evaluation metrics, validation context, deployment takeaway, and dominant caveat. Label structure, access conditions, missingness, and major data limitations are also recorded where they materially affect interpretation. This structure is used throughout the review to move beyond method cataloguing and toward a decision-oriented assessment of what each contribution actually establishes.

Each element of the coding logic serves a distinct interpretive purpose. The engineering problem identifies the operational question being addressed, such as short-horizon resource forecasting, constrained control, surrogate-assisted design, anomaly detection, or maintenance prioritization. The data regime captures the provenance and character of the evidence base, including whether the study relies on simulation, laboratory or tank measurements, short field campaigns, pilot deployments, or operational asset data. Representative inputs and output targets clarify what the model sees and what it is asked to estimate, predict, classify, or control. The model/representational family records the architecture or function class used to represent the mapping, while the decision/control/optimization framework records how predictions, surrogates, or learned policies are converted into engineering action. The baseline or comparator is treated as essential, because reported gains are only meaningful relative to an appropriate reference, whether that reference is persistence, harmonic analysis, a physical solver, a classical controller, or a simpler statistical or machine-learning model (Fituri et al., 2020; Qian et al., 2022; Serras et al., 2019).

The remaining fields govern interpretation of practical relevance. Evaluation metrics are recorded in their task-specific form rather than reduced to generic accuracy language. Validation context identifies the operational realism of the evidence, which is especially important in marine systems where many studies remain simulation- or laboratory-dominant (Alcibar et al., 2025; Badoe et al., 2022; Bisinotto et al., 2024; Chen et al., 2024b; Lin et al., 2024b). Deployment takeaway summarizes the most defensible practical implication of the result. Dominant caveat records the principal limitation that constrains transferability, robustness, or adoption, such as narrow site dependence, sparse failure labels, surrogate error, distribution shift, or insufficient real-world validation. This framework is used because algorithm labels alone are not sufficient for meaningful comparison; the same model family may carry very different evidentiary weight depending on the task, the data source, and the realism of the validation setting.

3.3. Evidence ladder and comparative interpretation

A central feature of the review is the E1–E5 evidence ladder (Table 3), which is used to make validation maturity explicit and to govern comparative interpretation across domains. The purpose of the ladder is not merely classificatory. It provides the main logic by which stronger and weaker forms of evidence are distinguished in a field where commercial maturity, data access, and operational exposure differ sharply between offshore wind, wave, tidal, and OTEC systems.

The five evidence levels are defined as follows. E1 denotes synthetic or numerical validation, in which the method is assessed entirely in a solver-based, simulated, or otherwise artificial environment. E2 denotes laboratory, basin, or tank validation, where the physical setting is controlled but still constrained relative to open-water operation. E3 denotes component-, rig-, or short-campaign validation, which introduces partial operational realism but remains limited in duration, scope, or generalizability. E4 denotes pilot or single-site operational validation, in which the model is tested on a real asset or bounded operational environment. E5 denotes multi-asset, multi-site, or long-duration operational validation, which provides the strongest basis for deployment-oriented conclusions.

Table 3
Evidence ladder for comparative interpretation.

Evidence level	Typical data source	Validation context	Engineering interpretation
E1	Synthetic/numerical data	Solver-based or fully simulated environment	Useful for concept testing and algorithmic feasibility, but not deployment evidence
E2	Laboratory/basin/tank data	Controlled physical environment	Useful for mechanism validation and constrained proof-of-concept demonstration
E3	Component/rig/short field campaign data	Partial operational realism	Promising evidence, but limited transferability and deployment generalization
E4	Pilot/single-site operational data	Real asset in bounded operational setting	Meaningful deployment relevance, though still site-specific
E5	Multi-asset/multi-site/long-duration operational data	Broad operational environment	Strongest maturity signal and best support for deployment-oriented conclusions

This ladder is central to the paper's comparative logic because marine renewable energy domains do not occupy the same maturity position. Offshore wind contains a much larger share of E4–E5 evidence than wave, tidal, or OTEC, largely because utility-scale assets generate richer operational datasets and support broader O&M workflows (Santos et al., 2022; Zhang et al., 2025b). Wave and tidal studies often provide meaningful technical progress but remain concentrated in E1–E3 settings, particularly in control and design (Badoe et al., 2022; Fituri et al., 2020; Qian et al., 2022). OTEC is still predominantly supported by experimental, rig-scale, or component-scale evidence (Kondeti and Palanisamy, 2025; Liu et al., 2024b; Rawat and Kumar, 2024; Xia et al., 2020). For that reason, cross-domain conclusions in this review are governed by validation maturity and data regime, not by algorithm labels alone. A method that appears strong under E1 or E2 conditions may still be far from deployment relevance, whereas a modest performance gain demonstrated under E4 or E5 conditions may be much more consequential from an engineering standpoint.

The ladder is also used to prevent false equivalence across task families. A forecasting model evaluated on long field records, a fault detector trained on operational SCADA streams, and a controller tested only in a simulated hydrodynamic environment should not be compared as though they provide the same kind of evidence. Throughout the review, reported performance is therefore interpreted through the joint lens of task family, baseline strength, data regime, and evidence level. This is the mechanism by which the review distinguishes algorithmic promise from operationally credible maturity.

3.4. Datasets, data regimes, and benchmarking logic

A rigorous interpretation of AI performance in marine renewable energy requires explicit attention to datasets and benchmarking conditions rather than model architecture alone (Alcibar et al., 2025; Díaz and Soares, 2020; Kisvari et al., 2021). Across wave, tidal, offshore wind, and OTEC applications, studies draw on markedly different combinations of operational measurements, field campaigns, laboratory or tank experiments, remote sensing, numerical simulations, and hybrid data products (Kondeti and Palanisamy, 2025; Serras et al., 2019). These differences shape sample size, temporal resolution, openness, label availability, missingness, drift, and reproducibility. They also affect both model choice and the strength of any reported claim. Reported error values or accuracies cannot be interpreted in isolation because they often reflect the convenience, scarcity, or maturity of the underlying data regime as much as the intrinsic merit of the algorithm itself.

Several dataset attributes are especially important. Openness and access matter because many of the strongest offshore-wind datasets remain proprietary, which limits direct reproducibility and cross-study comparability even when operational realism is high (Santos et al., 2022; Zhang et al., 2025b). Label availability is equally consequential: many monitoring and O&M problems are characterized by rare faults, weak labels, or healthy-only records, while design and forecasting tasks often depend on continuous targets rather than curated classes (M'Zoughi et al., 2024; Yan et al., 2025; Zhang et al., 2025b).

Table 4
Comparative benchmarking matrix across marine renewable energy AI domains.

Domain	Typical data sources	Typical data regime	Label/data constraints	Relevant baseline/ comparator families	Typical metrics	Typical highest evidence setting (E-level)	Common benchmarking issues	What should not be compared directly
Wave	Buoy and port records; site-specific wave-plant measurements; wave tanks and shaking tables; CFD/HOS/WEC simulations	Mixed field, lab/ tank, and simulation; long forecasting archives coexist with small experimental/ control datasets; resolutions from 15-min/hourly to sub-second	Sparse fault labels; rare extreme events; environmental noise; biofouling, aging, and buoy-position domain shift; some site-specific access limits	Persistence; climatology; numerical wave models; classical control baselines; hydrodynamic solvers	MAE/RMSE for forecasting; absorbed energy and constraint-violation measures for control; surrogate error and design-performance indicators for optimization; precision/ recall/F1 where diagnostics are studied	E3–E4 in forecasting; E1–E3 in control, design, and diagnostics	Mixing forecasting, control, and O&M results under one benchmark narrative; horizon-dependent baselines; synthetic or scarce fault labels	Long buoy/ hindcast forecasting studies versus CFD/tank control studies; synthetic-fault diagnostics versus operational monitoring
Tidal	ADCP/current profiles; long gauge records; sonar, HF radar, video; satellite imagery; CFD/ LES/BEM/FEM databases	Strongly site-specific and task-fragmented; combines long periodic series, campaign monitoring, and simulation-heavy design datasets	Underwater noise, rough-surface image interference, missing-flow reconstruction needs; labels range from ecological classes to integrity labels; many campaign-based datasets	Harmonic analysis; physical tidal models; engineering solvers; classical image-processing or monitoring baselines where applicable	MAE/RMSE for level/current forecasting; efficiency or solver-agreement metrics for design; precision/ recall/F1 for monitoring tasks	E2–E4 depending on task; strongest evidence in long gauge/ current forecasting and solver-consistent surrogate studies	Treating periodic forecasting, ecological classification, wake design, and blade optimization as if they shared one benchmark space	Simulation-only design/wake studies versus pilot/field evidence; semidiurnal forecasting versus monthly intrusion/ resource studies; site-specific radar/video results versus generalized claims
Offshore wind	SCADA; met-ocean and remote sensing; CMS/ vibration; lidar; simulation from aero-hydro-servo models and CFD/ LES; inspection imagery	Data-rich operational and simulation regime; single-turbine to multi-farm scale; 10-min SCADA, higher-frequency vibration, and simulation at kHz scale	Missing data, incomplete records, class imbalance, semantic ambiguity in O&M logs, concept drift; much data still private	Persistence; NWP-derived references; normal-behavior models; engineering wake models; high-fidelity solver references; simpler operational diagnostics	MAE/RMSE/ MAPE for forecasting; wake-loss or solver-agreement metrics for farm modeling; precision/ recall/F1/ AUROC/lead time for O&M	E4–E5 in operational forecasting and O&M; often E2–E4 in wake, surrogate, and layout studies	Cross-site comparisons confounded by different sensors and atmospheric/site conditions; curated image sets overstating field readiness	Public benchmark or multi-farm studies versus proprietary single-site studies; curated blade imagery versus real inspection workflows; simulation-only surrogates versus noisy field models
OTEC	Satellite thermal proxies; in situ profiles; numerical thermodynamic/ ocean models; rig data; limited operational thermal measurements	Low-data, proxy-heavy, and simulation-heavy; basin/ global profile datasets coexist with small local rig or industrial datasets	Sparse vertical observations; measurement bias; cloud interference; limited extreme-event operational access; anonymized industrial data; post-2020 reporting in this domain is explicitly thin	Thermodynamic solvers; physics-based estimators; compact supervised-regression baselines	MAE/RMSE for state estimation and prediction; agreement-with-experiment measures; efficiency- or performance-related indicators for optimization and control	E1–E3, with the strongest evidence arising from independent in situ validation and experimental rig studies	Ground truth often another model output; adjacent thermal applications mixed with direct OTEC evidence; weak public benchmark culture	Global/regional proxy-based regressions versus sparse operational OTEC studies; model-versus-model validation versus independent physical measurements

Missingness, drift, and heterogeneity further complicate interpretation, especially in offshore settings where sensor configurations differ across assets, maintenance records are inconsistently standardized, and environmental conditions shift over time. In such contexts, a model's apparent superiority may owe as much to dataset curation and problem framing as to the underlying learning method.

Benchmarking must therefore remain task-specific and evidence-aware. For forecasting, the minimum acceptable benchmark is not simply another black-box machine-learning model; it should include physically or operationally relevant baselines such as persistence, climatology, harmonic analysis, numerical wave or current models, or NWP-derived references, depending on the application. For control, the relevant criteria extend beyond predictive accuracy to include absorbed energy, net power, load or fatigue penalties, constraint violations, and computational latency. For design and optimization, meaningful comparison requires metrics such as AEP, LCOE-related indicators, constraint feasibility, cavitation or structural trade-offs, robustness under uncertainty, and surrogate error relative to the high-fidelity solver. For monitoring, maintenance, and fault diagnosis, precision, recall, F1 score, AUROC, false-alarm burden, lead time, and practical maintenance utility are more informative than raw accuracy alone.

Not all reported results are directly comparable, even when the same nominal method family is involved. A turbine-level offshore-wind predictor at 30-s resolution should not be compared naively with a 48-h farm forecast, a significant-wave-height predictor, a tidal-level estimator, or an OTEC heat-exchanger surrogate. Forecast horizon, sampling rate, operational risk, baseline difficulty, and validation setting differ too substantially. Likewise, an anomaly detector trained on healthy-only SCADA data is not directly comparable with a supervised classifier built on curated failure labels. The goal of the present review is therefore not to impose a single benchmark across all marine-energy AI tasks, which would be unrealistic, but to standardize how benchmark claims are interpreted in relation to task family, data provenance, and validation maturity. To make this benchmarking logic operational rather than purely discursive, Table 4 summarizes the main domain-specific differences in data provenance, data regime, labeling constraints, baseline expectations, typical metrics, highest current evidence setting, and direct-comparison limits across the four marine renewable domains. For additional transparency on cross-domain dataset visibility, temporal granularity, access conditions, and label structure, Appendix Table A1 provides a compact comparative data-visibility summary.

Taken together, this methodological framework positions the review as an evidence-weighted comparative synthesis rather than a method inventory. The literature is interpreted through a common coding logic, an explicit evidence ladder, and a dataset-aware benchmarking framework. This allows the review to compare studies from different domains on a technically consistent basis while preserving the distinctions that matter most for offshore engineering judgment: what problem is being solved, under what data conditions, against which baselines, with what realism of validation, and with what degree of deployment relevance.

4. Review of literature

4.1. Artificial intelligence in wave energy conversion (WEC)

4.1.1. Forecasting

In wave energy, forecasting is driven by a control imperative. The engineering problem is not merely to predict sea-state descriptors in the abstract, but to anticipate the wave conditions or excitation-force characteristics that matter for WEC operation, scheduling, and survivability (Freeman et al., 2021; Ramos-Marin and Guedes Soares, 2025). Typical inputs include buoy data, hindcast products, spectral features, and occasionally fused environmental covariates (Ali et al., 2024; Halicki et al., 2025; Kazeminezhad et al., 2025; Yanchin and Guedes Soares, 2024). Typical targets include significant wave height, energy period, wave-energy flux, and short-horizon excitation- or power-related quantities (Jamei et al., 2022; Yang et al., 2022; Zhang et al., 2024b). Classical baselines remain persistence models, ARIMA-type temporal models, and physics-based wave forecasts, whereas more recent studies use CNN/LSTM hybrids and bias-correction pipelines (Ali et al., 2024; den Bieman et al., 2023; Yanchin and Guedes Soares, 2024). The practical takeaway from the literature is that hybrid methods can improve short-horizon skill at a given site, especially when they correct biases in physical forecasts (Ali et al., 2024; den Bieman et al., 2023), but their performance often remains site-specific and vulnerable to seasonal or sea-state shift (Hasan et al., 2024; Raj and Prakash, 2024). Validation is still dominated by retrospective single-site studies rather than cross-site operational transfer tests (Bisinotto et al., 2024; Yanchin and Guedes Soares, 2024).

4.1.2. Control

Wave-energy control is the task in which AI appears most strategically important, because control choices directly affect absorbed energy, device motion, and structural loading (Freeman et al., 2021; Lin et al., 2024b). The core problem is sequential decision-making under irregular forcing and hard constraints (Anderlini et al., 2016; Zhang et al., 2024a). Classical reactive and predictive control methods remain essential benchmarks, and any learning-based method should be judged against them, not merely against other learned controllers (Anderlini et al., 2016; Umeda et al., 2024). Learning-based WEC control has combined neural surrogate models with control-layer approaches such as RL-based policy learning, adaptive control, and MPC-style constrained decision-making (Anderlini et al., 2020; Chen et al., 2024a; Lin et al., 2024b; Zhang et al., 2025c).

Post-2020 physics-informed learning strengthens this control discussion because WEC control is often data-limited but physically structured. PINN-style system identification and physics-informed surrogate learning are most relevant where they reduce model-form uncertainty or improve sample efficiency under irregular waves. However, their present role should remain bounded as E1–E3 support for system identification and constrained control rather than evidence of deployment-ready autonomous WEC control.

The deployment takeaway is therefore cautious: learning can improve control flexibility and reduce model-form dependence, but the current evidence does not support interpreting unconstrained black-box RL as close to routine offshore deployment (Badoe et al., 2022; Bisinotto et al., 2024; Shahroozi et al., 2024). Safety, sample efficiency, and sim-to-sea transfer remain central limitations (Bisinotto et al., 2024; Tang et al., 2024b).

4.1.3. Design and optimization

The design and optimization problem in wave energy is dominated by expensive evaluations (Azad et al., 2025; Katsidoniotaki et al., 2025). Hydrodynamic and CFD-informed design loops are costly enough that surrogate model families, such as response-surface or Gaussian-process-style surrogates, are often coupled with multi-objective evolutionary optimization (Azad et al., 2025; Sarkar et al., 2016; Zhao et al., 2024b). Neural operators and physics-informed surrogates can also be positioned here as post-2020 extensions of surrogate-assisted design: their value lies in accelerating repeated hydrodynamic or flow-response evaluations when many-query exploration is required. This should be framed as solver-accelerated or physics-informed design support, not as replacement of hydrodynamic validation. Typical inputs are geometry, PTO parameters, wave-climate summaries, and array-layout variables; outputs are AEP, capture width, structural load proxies, or LCOE-related performance measures (Azad et al., 2025; Huang et al., 2024; Lin et al., 2024a). Here the deployment takeaway is clear: AI is useful first as an accelerator of design-space exploration, not as a replacement for physics (Azad et al., 2025; Sarkar et al., 2016). Surrogate error, constraint handling, and uncertainty propagation into techno-economic metrics are the main caveats, and these are often underreported in the literature (Katsidoniotaki et al., 2025; Zou et al., 2022).

4.1.4. Operation & Maintenance and reliability

Wave-energy O&M is economically important but evidence-poor (Bao et al., 2024; Freeman et al., 2021). The engineering problems include PTO anomaly detection, mooring and structural health assessment, and degradation-aware maintenance scheduling under sparse labels (Bao et al., 2024; Boutkhil Mohamed et al., 2025; Kang et al., 2024). Inputs can include vibration, strain, acoustic signatures, or power traces, while targets are typically fault class, anomaly score, or maintenance priority (Bao et al., 2024; Lu et al., 2022; Sacie et al., 2022). Across these studies, the decisive limitation is not whether the classifier is tree-based, kernel-based, or deep, but whether it is trained and tested on failure modes that resemble offshore degradation under realistic sensor drift, repair history, and environmental variability (Bao et al., 2024; Sacie et al., 2022; Yanchin and Guedes Soares, 2024). The dominant limitation is not a lack of algorithms but a lack of long-duration failure-labeled offshore datasets (Bao et al., 2024; Boutkhil Mohamed et al., 2025). Consequently, many wave O&M studies remain proof-of-concept, and the literature must be interpreted with that maturity boundary in mind (Boutkhil Mohamed et al., 2025; Kang et al., 2024). Table 5 shows that the apparent breadth of AI in wave energy masks a sharp maturity split. Forecasting is the most defensible near-term role where site-level records and physical or statistical baselines exist. Control and design are strategically important but remain dominated by E1–E3 validation, so their proper interpretation is constrained proof of concept or design acceleration rather than offshore deployment readiness. O&M is the weakest evidence area because long-duration, failure-labeled offshore records are scarce.

4.2. Artificial intelligence in tidal energy

4.2.1. Forecasting

In tidal energy, the forecasting problem differs from wave energy because the underlying resource has stronger physical periodicity (Bradbury and Conley, 2021; Kotta et al., 2020). That does not remove the need for AI; it changes where AI is useful. Machine learning is most valuable when meteorology, turbulence, stratification, or local site effects perturb the nominally predictable tidal signal (Qian et al., 2022; Sun et al., 2024). Typical inputs include tidal levels, current records, ADCP measurements, and meteorological covariates (Bradbury and Conley, 2021; Qian et al., 2022; Sun et al., 2024). Targets include tidal levels, tidal-current magnitude and direction, and site-level resource indicators (Liang et al., 2021; Qian et al., 2022; Zhang et al., 2023b). In this context, AI should be evaluated against harmonic-analysis or physically structured baselines, not treated as an automatic substitute for them (Aly, 2020; Qian et al., 2022; Sun et al., 2024). The literature suggests that deep temporal models can improve short-horizon prediction under disturbed conditions, but operational generalization remains site-sensitive (Bradbury and Conley, 2021; Liang et al., 2021; Sun et al., 2024). Accordingly, tidal forecasting should be judged by whether AI adds value beyond harmonic and physics-based baselines under disturbed or site-specific conditions, not by whether it outperforms another black-box model on a single split.

4.2.2. Control

The control problems in tidal energy include barrage gate scheduling, dispatch over tidal cycles, and adaptive turbine control under turbulence and flow reversal (Fang et al., 2023; Rashid et al., 2024a). The engineering objective is typically a trade-off among energy capture, structural loading, and operational constraints (Moreira et al., 2022; Rashid et al., 2024a). Reinforcement learning and adaptive control have been proposed, but the evidence base remains modest and mostly simulation-centered (Fang et al., 2023; Rashid et al., 2024a). The deployment takeaway is therefore narrower than in offshore wind O&M: RL-style tidal control is an active research direction, not an operationally mature one (Badoe et al., 2022; Fang et al., 2023). Its value is highest where decisions are sequential, constrained, and difficult to optimize analytically, but safe exploration and site-specific hydrodynamic dependence remain significant barriers (Badoe et al., 2022; Rashid et al., 2024b).

4.2.3. Design and optimization

Tidal-turbine design and siting are well suited to surrogate-assisted optimization because the hydrodynamics are expensive to resolve and array interactions matter (Li et al., 2024b; Sun et al., 2019; Xu et al., 2024b). Inputs typically include blade or hydrofoil geometry, inflow characteristics, blockage or bathymetry descriptors, and in some studies array-layout variables (Li et al., 2024a; Tahani and Babayan, 2019; Xu et al., 2024a). Targets include power coefficient, hydrodynamic efficiency, cavitation margin, fatigue or structural metrics, and broader techno-economic outcomes (Sun et al., 2019; Xu et al., 2024b; Zhu et al., 2020). The main deployment takeaway is that AI is already useful here as a computational enabler (Li et al., 2024b; Tahani and Babayan, 2019). However, claims should remain conditional on solver fidelity, uncertainty propagation, and validation against in situ flow conditions (Almoghayer et al., 2024; Badoe et al., 2022). Too many optimization studies still stop at numerical evidence (Xu et al., 2024a; Zhang et al., 2024c). At present, however, surrogate-assisted and frontier AI design workflows should be treated as a plausible methodological direction rather than a mature tidal-AI evidence base; direct tidal validation remains necessary before such approaches can support deployment-level claims.

4.2.4. Operation & Maintenance and reliability

Tidal O&M is dominated by corrosion, biofouling, underwater visibility constraints, and limited access windows (Habbouche et al., 2024; Rashid et al., 2024b). Accordingly, the most active AI applications are image-based fouling detection, anomaly detection from vibration or acoustic streams, and monitoring support tools (Chen et al., 2024b; Habbouche et al., 2024; Rashid et al., 2024b). The engineering significance of this work is that tidal O&M has a narrower but concrete AI niche: biofouling and underwater inspection create small, noisy, imbalanced image datasets where transfer learning and augmentation are useful only if they improve field-relevant detection under turbidity, changing illumination, and uncertain labels (Rashid et al., 2024b). The relevance of generative models in tidal O&M should be limited to narrow data problems such as augmentation under small, noisy, imbalanced biofouling or inspection-image datasets. Such augmentation is useful only if it improves field-relevant detection under turbidity, changing illumination, and uncertain labels, rather than simply improving offline classification on curated images. These are practically relevant studies because they address a real class-imbalance and data-scarcity problem rather than applying computer vision in the abstract (Habbouche et al., 2024; Rashid et al., 2024b). The caveat is that underwater imagery remains noisy, labels are difficult to curate, and long-horizon maintenance economics are still less well quantified than short-term classification performance (Chen et al., 2024b; Habbouche et al., 2024). Table 6 highlights that tidal-energy AI is not immature because the resource is unimportant, but because the evidence base is fragmented across periodic forecasting, local hydrodynamic modeling, biofouling surveillance, and simulation-heavy design. The strongest claims are task-specific: forecasting can be useful when local perturbations weaken harmonic baselines; design tools can accelerate expensive hydrodynamic evaluations; monitoring remains label- and visibility-constrained.

4.3. Artificial intelligence in offshore wind energy farm

4.3.1. Forecasting

Offshore wind is the strongest-evidence AI domain in marine renewables because the engineering problems are embedded in mature industrial assets and comparatively rich data streams (Díaz and Soares,

Table 5
Decision-oriented synthesis of AI applications in wave energy.

Task	Engineering problem	Typical inputs	Dataset regime & source	Output target	Model family and decision/control framework	Meaningful baselines	Metrics	Validation level	Main benefit	Dominant caveat/ failure mode
Forecasting	Short-horizon prediction of wave state or wave-energy variables for WEC scheduling, dispatch support, and survivability-aware operation	Buoy observations, hindcast archives, spectral features, wave height/period histories, occasional environmental covariates	Mostly site-specific historical wave records; field buoy datasets for forecasting; limited cross-site operational data	Significant wave height, wave energy period, wave-energy flux, short-term wave power, excitation-force-related quantities	**Model/ representational family:** ANN/MLP; CNN/LSTM hybrids; ELM; ANFIS/FIS hybrid predictors; GPR/Gaussian-process-style models; hybrid decomposition + ML predictors. **Decision/control/ optimization framework:** Not applicable, except downstream WEC scheduling support	Persistence models, ARIMA-type temporal models, physics-based wave forecasts, harmonic/ statistical baselines where applicable	MAE, RMSE, nRMSE, MAPE, relative error reduction versus physical/ statistical baseline	E2–E4	AI is most useful as a site-level short-horizon forecasting enhancer, especially when hybridized with physical forecasts	High site dependence; weak cross-site transfer; regime-shift sensitivity across seasons and sea states; limited operational generalization beyond the training site
Control	Real-time or near-real-time PTO and device control under irregular seas, with energy-maximization subject to motion, safety, and survivability constraints	Device state, wave excitation, PTO state, hydrodynamic state estimates, simulated or tank-derived control-state variables	Mostly simulation and lab/tank studies; occasional digital-twin or constrained experimental evidence; almost no broad operational field evidence	PTO damping coefficient, generator torque, control action, absorbed energy, constrained motion response	**Model/ representational family:** ANN-based predictors or neural surrogates; fuzzy/ neuro-fuzzy models. **Decision/control/ optimization framework:** RL-based control, including Q-learning, LSPI, and DRL when used for PTO policy learning; MPC with learned surrogates; adaptive dynamic programming; reactive/latching-control comparators	Reactive control, latching control, classical MPC, expert-tuned rule-based control, Q-learning/SARSA in comparative RL studies	Net absorbed energy, constraint-violation rate, load penalty, runtime/ computational burden, energy improvement relative to baseline	E1–E3	Learned predictors or learned policies are valuable when they improve control adaptivity or reduce model mismatch inside constrained WEC control loops	Sim-to-sea transfer remains weak; exploration safety, sample efficiency, and deployment-grade robustness remain major barriers
Design and optimization	Accelerated search over WEC geometry, PTO parameters, farm layout, and techno-economic trade-offs under expensive hydrodynamic/ CFD evaluation	Device geometry, PTO parameters, wave-climate summaries, array-layout variables, solver outputs	Predominantly simulation-driven or surrogate-assisted design data; numerical studies dominate	AEP, capture width, hydrodynamic efficiency, load proxies, cost indicators, LCOE-related performance	**Model/ representational family:** ANN surrogates; GPR/ Gaussian-process-style surrogates; response-surface or other surrogate models. **Decision/control/ optimization framework:** surrogate-assisted optimization; GA; MOGA/NSGA-style multi-objective optimization; hybrid ML–optimization loops	Direct CFD/ hydrodynamic simulation, heuristic/manual design, classical numerical optimization without learned surrogate	AEP, LCOE, efficiency gain, optimization runtime, solver-agreement error, load/cost trade-off indicators	E1–E3	Surrogate models coupled with optimization frameworks are most defensible as computational accelerators for design-space exploration rather than replacements for physics	Surrogate error is often underreported; uncertainty propagation into LCOE and reliability is often weak; results remain solver-dependent

(*continued on next page*)

Table 5 (*continued*)

Task	Engineering problem	Typical inputs	Dataset regime & source	Output target	Model family and decision/control framework	Meaningful baselines	Metrics	Validation level	Main benefit	Dominant caveat/ failure mode
O&M and reliability	Early fault detection and maintenance prioritization for PTOs, moorings, turbines, and structural subsystems under sparse-failure conditions	Vibration, strain, acoustic data, power signals, acceleration, structural-response traces	Sparse-failure, site-specific monitoring data; mostly proof-of-concept datasets; very limited long-duration offshore labeled failure records	Fault class, anomaly score, maintenance need, remaining health state	**Model/ representational family:** SVM/kernel models; RF/GB/ XGBoost tree-based models; MLP; ResNet/ deep classifiers; ensemble models. **Decision/support framework:** condition-monitoring workflow; anomaly-detection workflow; maintenance-prioritization support	Threshold-based alarms, simpler statistical diagnostics, manual/physics-informed inspection logic where available	Accuracy, F1, precision/recall, false alarms, class-wise fault identification performance	E2–E3	Classification and anomaly-detection models are useful for moving from reactive repair to condition-based maintenance where relevant signals exist	Rare-failure labels are scarce; sensor drift after replacement/ repair weakens stability; operator trust and explainability remain limited

Table 6
Decision-oriented synthesis of AI applications in tidal energy.

Task	Engineering problem	Typical inputs	Dataset regime & source	Output target	Model family and decision/control framework	Meaningful baselines	Metrics	Validation level	Main benefit	Dominant caveat/ failure mode
Forecasting	Short-horizon prediction of tidal levels, currents, and energy-related resource variables under site-specific hydrodynamic and meteorological perturbations	ADCP measurements, tidal-height records, current profiles, meteorological variables, astronomical tidal inputs	Site-specific field measurements combined with simulation or partial observational data; some hybrid simulation/field datasets	Water-level prediction, current magnitude/ direction, short-term tidal-energy forecast, resource estimation	**Model/ representational family:** ANN/MLP; H-ELM + LSTM; Bi-LSTM; CNN/LSTM temporal models; hybrid residual/ fuzzy time-series predictors. **Decision/ control/optimization framework:** Not applicable, except operational forecast-correction support	Harmonic analysis, UTide-type baselines, numerical/ physical tidal models, simpler recurrent/ statistical baselines	MAE, RMSE, relative error reduction, cm-level forecast error, short-horizon forecast improvement	E1–E4	AI is useful when local disturbances or weather-driven deviations limit the adequacy of purely harmonic or deterministic models	Strong periodic prior means AI must beat structured baselines, not just other ML models; generalization remains site-sensitive
Control	Sequential control of barrages, tidal stream turbines, or adaptive operating policies under flow reversal, turbulence, and load constraints	Tidal state variables, gate/ turbine operating states, current fields, control states	Mostly simulation-based or limited pilot-scale control evidence; little long-duration operational RL/ control evidence	Dispatch/gate opening, turbine control action, operating policy, energy capture under constraints	**Model/ representational family:** neural predictors or policy approximators; fuzzy/ neural models where used. **Decision/ control/optimization framework:** RL-based control; DRL-style control; adaptive control; operating-policy optimization	Historical expert schedules, rule-based control, classical dispatch/ control methods	Energy gain, policy performance relative to historical or expert baseline, constraint satisfaction, robustness	E1–E3	AI is promising where the control problem is sequential and analytically difficult	Evidence is still limited; safe exploration and field transfer remain unresolved
Design and optimization	Hydrofoil/blade design, turbine placement, and array optimization under expensive hydrodynamic evaluation and multiple competing objectives	Candidate hydrofoil/blade profiles, bathymetry, inflow/turbulence descriptors, array-layout variables	Mostly simulation-heavy design studies and surrogate-assisted workflows	Selected hydrofoil section, power coefficient, efficiency, wake-aware array performance, cavitation/load trade-offs	**Model/ representational family:** ANN surrogates; hydrodynamic or wake surrogate models. **Decision/control/ optimization framework:** ACO; multi-objective evolutionary optimization; surrogate-assisted design search	Manual section selection, CFD-only search, classical numerical optimization	Power coefficient, efficiency gain, optimization runtime, trade-off quality, solver agreement	E1–E3	AI is already useful as a computational enabler for tidal design-space exploration	Many gains remain numerical; field-backed design validation is limited; uncertainty propagation is weak
O&M, biofouling, and monitoring	Detection of biofouling, attachment growth, anomalies, and condition deterioration in a difficult underwater maintenance environment	Underwater imagery, sonar, vibration/ acoustic signals, short monitoring campaigns	Sparse-label, small-data, often noisy underwater datasets; short campaigns dominate	Fouling class/ extent, anomaly score, attachment recognition, maintenance trigger	**Model/ representational family:** CNNs; GAN/ generative models where used; anomaly-detection models. **Enabling/training/ workflow layer:** transfer-learning workflow; GAN-assisted augmentation for class imbalance; image-processing + ML inspection pipeline	Manual inspection, classical computer vision, threshold-based monitoring	Precision, recall, F1, false positives, anomaly-detection performance	E2–E3	AI is valuable for targeted surveillance and maintenance prioritization where manual inspection is costly and difficult	Underwater visibility/noise, class imbalance, weak label quality, and limited long-term maintenance-economic evidence remain major constraints

Table 7
Decision-oriented synthesis of AI applications in offshore wind.

Task	Engineering problem	Typical inputs	Dataset regime & source	Output target	Model family and decision/control framework	Meaningful baselines	Metrics	Validation level	Main benefit	Dominant caveat/failure mode
Forecasting	Turbine-level and farm-level wind/power prediction under wake interaction, operational planning, and reserve/dispatch constraints	SCADA, NWP products, neighboring-turbine signals, met-ocean covariates, lidar where available, high-frequency or aggregated turbine data	Richest data regime among the four domains; mostly private operational datasets, often single-farm or single-operator, with varying sampling horizons	Hub-height wind, turbine active power, farm power, wake-aware short-horizon predictions	**Model/representational family:** spatiotemporal GNNs/graph-learning models; Transformer hybrids; CNN/RNN/LSTM-type models; normal-behavior predictive models; NWP-correction hybrid predictors. **Decision/control/optimization framework:** forecasting workflow; normal-behavior monitoring support where used operationally	Persistence, power-curve baselines, MLP/LSTM non-graph baselines, NWP-only forecasts	MAE, MAPE, RMSE, energy-ratio error, normal-behavior deviation metrics	E4–E5	Offshore wind currently offers the clearest deployment-oriented evidence for AI forecasting, especially where inter-turbine dependence is modeled explicitly	Cross-farm transfer remains difficult; datasets are proprietary and heterogeneous; label and sampling conventions vary
Control and farm coordination	Farm-level interaction management, wake-aware coordination, turbine/farm control under coupled aerodynamic effects	SCADA, neighborhood/turbine interaction signals, wake surrogates, operational state histories, simulated flow fields	Mixed regime: operational SCADA for monitoring/prediction, but many control-oriented wake studies still rely heavily on simulated data or surrogate flows	Control action, yaw coordination, wake-aware power response, farm-level operating strategy	**Model/representational family:** GNN/graph-learning models; wake surrogate models; neural-operator or operator-learning surrogates. **Decision/control/optimization framework:** multi-agent or coordinated control; RL-based or RL-inspired wake coordination; wake-aware farm-control framework	Turbine-level independent control, non-graph predictive models, classical wake-control strategies	Power gain, wake-loss reduction, MAE/RMSE for surrogate prediction, control performance indicators	E2–E4	Graph-learning and operator-learning surrogate models improve the representation of wake-coupled farm interactions, while the farm-control frameworks built on them still require stronger field validation	Many promising results still depend on simulated wake data rather than field-tested control experiments
Design and optimization	Layout, substructure, cable, and multi-objective design optimization under expensive aero-hydro-servo-elastic evaluation	Layout variables, cable topology, turbine/substructure parameters, wake-loss calculations, solver outputs	Simulation-heavy, solver-in-the-loop design studies; industrial relevance high but operational comparative validation weaker than O&M	AEP, wake loss, cost, substructure performance, design trade-offs	**Model/representational family:** ANN surrogates; GP/GPR surrogates; other solver-trained surrogate models. **Decision/control/optimization framework:** Bayesian optimization; GA/PSO/DE/NSGA-style evolutionary or swarm search; surrogate-assisted optimization	Direct high-fidelity simulation, manual or classical optimization baselines	AEP, LCOE, efficiency/cost trade-off, constraint feasibility, surrogate error	E1–E3	AI is useful here primarily as a computational accelerator within physically grounded design loops	Surrogate fidelity and uncertainty handling must remain explicit; AI should not be presented as replacing verified engineering models
O&M and reliability	Fault detection, anomaly detection, lead-time estimation, maintenance prioritization, inspection support, and reliability-informed decision-making	SCADA, condition-monitoring signals, alarms, vibration/temperature data, maintenance logs, blade imagery, drone inspection data	Strong operational regime relative to other domains, but still heterogeneous, proprietary, and label-limited	Fault class, anomaly score, maintenance label, lead-time estimate, inspection finding, reliability-informed action	**Model/representational family:** autoencoders; Transformer/log-analysis models; computer-vision inspection models; LLM/VLM foundation models where used **Decision/support workflow:** normal-behavior monitoring; SCADA-based anomaly-detection workflow; inspection triage; maintenance decision support; human-in-the-loop O&M support	Threshold alarms, simple statistical diagnostics, manual log coding, classical CV pipelines, simpler ML baselines	Precision, recall, F1, AUROC, false alarms, lead time, maintenance utility	E4–E5	This is the strongest current deployment-oriented AI use case across all four domains	Cross-farm transfer, label quality, alarm inconsistency, dataset opacity, and model drift remain major challenges

Table 8
Decision-oriented synthesis of AI applications in OTEC.

Task	Engineering problem	Typical inputs	Dataset regime & source	Output target	Model family and decision/control framework	Meaningful baselines	Metrics	Validation level	Main benefit	Dominant caveat/failure mode
Forecasting	Prediction of cycle/component state under changing thermal and hydraulic conditions in low-data OTEC systems	Surface/deep-water temperatures, flow rates, pressures, heat-exchanger variables, low-dimensional operating signals	Low-data, experimental-platform, rig-scale, or pilot-like subsystem data; often no long-duration fleet-scale operational records	Heat-transfer performance, system state, cycle response, component behavior	**Model/representational family:** ANN/MLP; LSTM; compact process surrogates; selected hybrid physics-aware models **Decision/control/optimization framework:** state-estimation and process-prediction support	Thermodynamic solvers, simplified experimental correlations, rule-based process estimation	MAE, RMSE, agreement with experiment, prediction error	E2–E3	AI is useful as a compact predictive tool in data-constrained experimental or pilot OTEC settings	Evidence is still small-scale and pilot-heavy; broad operational generalization is not established
Supervisory control	Adjustment of flow rates, pumping conditions, and operating setpoints under narrow thermodynamic margins	Temperatures, pressures, pump states, flow rates, process-state signals	Mostly experimental platforms, simulation studies, or subsystem-level operating records	Supervisory control action, operating setpoint, controlled process response	**Model/representational family:** ANN/LSTM process surrogates; hybrid process models **Decision/control/optimization framework:** supervisory control support; setpoint adjustment; rule-based process-control comparison	Rule-based control, classical thermodynamic supervisory logic	Process error, setpoint-tracking quality, efficiency-related performance	E2–E3	Hybrid/compact learned models are promising when process structure is known but data are limited	The literature is still too small to justify strong maturity claims; operational robustness is underexplored
Design and supervisory optimization	Maximization of thermodynamic performance under a narrow temperature gradient and strong hydraulic constraints	Experimental-platform data, low-dimensional process variables, design and operating setpoints	Experimental or pilot-scale design/optimization data	Net power, heat-exchange efficiency, operating setpoints, cogeneration performance	**Model/representational family:** ANN/LSTM surrogates; hybrid thermodynamic/process models **Decision/control/optimization framework:** thermodynamic optimization; supervisory optimization; manual or rule-based tuning comparison	Thermodynamic solver, rule-based optimization, manual tuning	MAE, RMSE, efficiency gain, agreement with experiment	E2–E3	AI is most defensible here as a compact optimizer embedded in experimental design loops	Pilot-heavy evidence; optimization results should not be overstated as broad sector deployment evidence
O&M and reliability	Detection/prognosis of fouling, heat-exchanger degradation, pump anomalies, and subsystem deterioration in costly offshore access conditions	Heat-exchanger signals, flow/pressure anomalies, subsystem monitoring variables, sparse pilot data	Very limited published AI evidence; mostly inferred research opportunity rather than mature evidence base	Anomaly score, degradation indicator, maintenance need	**Model/representational family:** physics-aware/hybrid prognostic models; anomaly-detection models where available **Enabling/decision-support workflow:** digital-twin-supported prognosis workflow; maintenance decision support	Manual process monitoring, classical process diagnostics	Case-dependent; not yet standardized across the literature	E1–E2	OTEC is a natural candidate for hybrid digital-twin and physics-aware prognosis because the process is structured and access is costly	Published evidence remains sparse; this is still a research gap rather than an established AI subfield

Table 9
Post-2020 AI frontiers and their engineering relevance in marine renewable energy.

Methodological frontier	Engineering bottleneck addressed	Most relevant domain	Typical data regime	Current evidence maturity	Main limitation	Recommended validation step	How it changes engineering interpretation
PINNs/physics-informed learning	Sparse measurements, extrapolation beyond observed sea states, physically consistent system identification, and constrained control	Wave energy; OTEC; selected tidal and offshore-wind surrogate settings	Experimental, tank, rig, simulation, or sparse field data combined with governing equations or physical priors	Mostly E1–E3; strongest current wave evidence in system identification and constrained control	Sensitive to imperfect physics, boundary/noise assumptions, parameter identifiability, and training instability	Compare against first-principles, grey-box, and data-only baselines under regime shifts and noisy measurements	Shifts interpretation from black-box interpolation toward physics-constrained inference, but not toward deployment maturity without field validation
Neural operators/operator learning	Many-query approximation of parameterized physical responses, especially flow or wake fields needed for fast design/control evaluation	Offshore wind strongest; potential future use in wave/tidal arrays and OTEC process surrogates	Solver-generated fields, high-fidelity simulations, digital-twin workflows, limited operational anchoring	Mostly E1–E3/E4 depending on validation source; strongest in offshore-wind wake-surrogate studies	Generalization across geometries, inflow regimes, layouts, and measurement noise remains uncertain	Test across unseen layouts, inflow conditions, turbulence regimes, and field-informed benchmarks	Changes engineering interpretation from one-off prediction to reusable surrogate evaluation for design, control, and digital-twin workflows
Graph learning/GNNs	Coupled-device interactions, wake directionality, nonlocal farm/array dependence, and sensor-network structure	Offshore wind strongest; conceptually relevant to tidal arrays and wave farms	SCADA, farm-layout data, wake simulations, graph-structured sensor or asset networks	E3–E5 in selected offshore-wind forecasting/O&M contexts; weaker outside offshore wind	Graph structure may be arbitrary, unstable, or physically under-justified when array data are sparse	Validate graph definitions against physical layout, flow direction, wake interaction, and cross-site transfer	Moves interpretation from independent-device modeling toward relational system modeling
Generative models/diffusion models	Rare faults, severe class imbalance, missing telemetry, incomplete inspection data, and anomaly-sensitive monitoring	Offshore wind O&M strongest; tidal biofouling/image augmentation selectively relevant	SCADA streams, condition-monitoring data, inspection images, sparse or imbalanced fault datasets	Selective E3–E4 in offshore-wind condition monitoring; mostly exploratory elsewhere	Synthetic or reconstructed data may not preserve operational failure physics; can inflate offline metrics	Evaluate generated/reconstructed outputs against operational events, downstream maintenance utility, and distribution-shift tests	Shifts interpretation from simple classification to distribution-aware monitoring, imputation, anomaly detection, and uncertainty-sensitive support
Foundation models/LLMs/VLMs	Unstructured logs, inspection reports, work orders, imagery, maintenance histories, and multimodal evidence integration	Offshore wind O&M strongest; broader marine O&M remains emerging	Maintenance logs, inspection images, work orders, sensor summaries, retrieved historical records	Emerging; mostly workflow-support evidence rather than autonomous decision evidence	Hallucination, provenance loss, weak grounding, domain terminology errors, and overreliance risks	Use retrieval-grounded, auditable, human-in-the-loop evaluation with abstention and expert review	Reframes AI from only numerical prediction toward maintenance information management and decision-support workflows
Self-supervised learning/representation learning	Weak labels, healthy-only records, partially labeled SCADA streams, inspection images, and maintenance logs	Offshore wind strongest; wave/tidal monitoring potentially relevant	Large unlabeled or weakly labeled sensor streams, imagery, logs, and multivariate time series	Emerging; often pretraining or representation stage rather than direct deployment evidence	Representation quality may not translate into task-level engineering value	Evaluate downstream forecasting, anomaly detection, inspection, or maintenance tasks against supervised and simpler baselines	Changes interpretation from label-dependent supervised learning toward reusable representations under limited labels

2020; Kisvari et al., 2021; Mwangi et al., 2024). Forecasting spans multiple scales: hub-height wind prediction, turbine-level power prediction, wake-aware farm power prediction, and anomaly-aware normal-behavior modeling (Acikgoz and Korkmaz, 2025; Liu et al., 2023; Song et al., 2024). Typical inputs range from NWP products and farm-level SCADA to met-ocean covariates and neighboring-turbine signals (Kang et al., 2019; Pan et al., 2024; Rouholahnejad and Gottschall, 2025). Within this setting, graph learning becomes engineering-relevant because wind farms are relational systems in which turbine outputs and loads depend on wake directionality, layout, and neighboring-device influence (Dong et al., 2024; Liu et al., 2023; Pierrot and Pinson, 2025). The practical lesson from the recent literature is that the strongest offshore-wind forecasting gains now come less from replacing all physics with deep learning and more from better representing inter-turbine dependence and abnormal behavior (Kang et al., 2019; Liu et al., 2023; Pierrot and Pinson, 2025). Typical baselines remain persistence, power-curve models, non-graph MLP/LSTM models, and NWP-only forecasts, while the most informative metrics are MAE, MAPE, RMSE, and energy-ratio error (Acikgoz and Korkmaz, 2025; Melalkia et al., 2025; Rouholahnejad and Gottschall, 2025). Validation in this domain is stronger than in the other three domains, but cross-farm transfer and data-standardization problems remain significant (Quevedo-Reina et al., 2025; Rouholahnejad and Gottschall, 2025).

4.3.2. Control and farm coordination

The control problem in offshore wind is moving from turbine-level regulation toward farm-level interaction management (Zhao et al., 2024b; Zhu et al., 2024). At one end are classical turbine controls and normal-behavior models; at the other end are wake-aware farm controls, coordinated yawing, and power-loss analysis (Zhang and Zhao, 2023; Zhao et al., 2024b). Here the data structure is relational: neighboring turbines affect each other through wake propagation and blockage (Liu et al., 2023; Zhang and Zhao, 2023). This is why graph models and operator-learning surrogates have become important (Liu et al., 2023; Pierrot and Pinson, 2025). The main outputs in this literature are yaw-control settings, wake-aware power response, local-flow or load estimates, and farm-level operating actions under coupled aerodynamic conditions (Zhang and Zhao, 2023; Zhu et al., 2024). Neural-operator and operator-learning surrogates are most defensible in offshore wind when the bottleneck is repeated wake-field evaluation for layout, control, or digital-twin use. Their current maturity should be distinguished from field-tested closed-loop farm control: many operator-learning results remain solver-trained or simulation-backed and therefore support fast surrogate evaluation more strongly than autonomous control deployment. Meaningful baselines remain turbine-level independent control, non-graph predictive models, and classical wake-control strategies (Zhang and Zhao, 2023; Zhu et al., 2024). The most informative metrics are wake-loss reduction, power gain, surrogate-prediction error, and constraint-aware control performance under realistic operating conditions (Zhang and Zhao, 2023; Zhu et al., 2024). Graph-based and surrogate-assisted approaches are natural for wake-coupled farm coordination, but many remain closer to E2–E4 surrogate or simulation-backed evidence than to long-duration field-tested closed-loop control (Dong et al., 2024; Liu et al., 2023). The caveat is that much of the wake-surrogate and coordination literature still relies on simulated training data or indirect operational evidence rather than field-annotated control experiments, so validation maturity remains lower than in offshore-wind O&M and forecasting (Zhang and Zhao, 2023; Zhao et al., 2024b).

4.3.3. Design and optimization

Offshore-wind design and optimization problems are computationally expensive and multi-objective: layout, cable topology, substructure choices, wake losses, and fatigue must all be traded off (Ghosh et al., 2018; Shende et al., 2023; Wu et al., 2014). This makes the sector fertile ground for surrogate-assisted optimization, Bayesian optimization, and evolutionary algorithms (Quevedo-Reina et al., 2025; Wang et al., 2025c; Zhao et al., 2024c). Typical inputs in this task family include layout variables, cable-routing parameters, turbine and substructure descriptors, wake-loss calculations, and high-fidelity solver outputs (Lee et al., 2015; Wang et al., 2025c; Wu et al., 2014). The main outputs are AEP, wake loss, cost, structural trade-offs, and broader techno-economic indicators such as LCOE-related performance (Ghosh et al., 2018; Lee et al., 2015; Shende et al., 2023). Meaningful baselines are direct high-fidelity simulation, solver-in-the-loop optimization, and classical numerical optimization without learned surrogates (Lee et al., 2015; Quevedo-Reina et al., 2025; Zhao et al., 2024c). The most relevant metrics are AEP improvement, wake-loss reduction, cost or LCOE trade-off, constraint feasibility, and surrogate error relative to the underlying physical model (Quevedo-Reina et al., 2025; Wang et al., 2025c). AI is most defensible here when it accelerates design exploration while preserving a high-fidelity solver in the loop (Wang et al., 2025a; Zhao et al., 2024c). It is least defensible when a black-box surrogate is treated as if it were a verified engineering model in its own right (Quevedo-Reina et al., 2025). The combination of optimization framework, physical simulator, and uncertainty treatment therefore matters more than the label attached to the surrogate (Quevedo-Reina et al., 2025; Rouholahnejad and Gottschall, 2025).

4.3.4. Operation & Maintenance and reliability

Operation & Maintenance (O&M) is the area in which offshore wind already has the clearest deployment relevance (Bashir et al., 2022; Santos et al., 2022; Zhang et al., 2025d). The engineering problems include anomaly detection, fault identification, lead-time estimation, maintenance sequencing under weather windows, and inspection prioritization (Li et al., 2016; Pinciroli et al., 2021; Santos et al., 2022; Zhang et al., 2025d). SCADA-based condition monitoring continues to be a major backbone, partly because it uses existing instrumentation and partly because maintenance cost pressure is high (Díaz and Soares, 2020; Kisvari et al., 2021; Mwangi et al., 2024). Recent reviews still identify data-quality heterogeneity, label scarcity, and standardization deficits as central problems, but they also confirm that SCADA-based monitoring is now an established subfield (Santos et al., 2022; Su et al., 2024; Zhang et al., 2025c). For operators, the value of these models is therefore not generic classification accuracy, but earlier warning, lower false-alarm burden, better prioritization of inspections, and more reliable maintenance sequencing under weather-window and vessel-availability constraints. Generative and diffusion-based models should be linked here to rare faults, missing telemetry, and imbalance-sensitive condition monitoring. Their value lies in anomaly-sensitive monitoring, imputation, or fault-localization support, but generated or reconstructed data should not be assumed to preserve operational failure physics without validation against real events and maintenance outcomes. LLM/VLM-supported O&M should also be framed as a human-in-the-loop workflow layer for maintenance logs, inspection imagery, work orders, and retrieved historical records. Its defensible contribution is improved information organization, triage, and auditable decision support rather than autonomous offshore maintenance intelligence. The deployment takeaway is strong but not unqualified: models must be calibrated to changing turbine condition, alarm and maintenance records must be cleaned, and cross-farm transfer cannot be assumed (Quevedo-Reina et al., 2025; Rouholahnejad and Gottschall, 2025; Zhang et al., 2025d). Table 7 should be read as evidence of uneven maturity within offshore wind itself. Forecasting and O&M provide the strongest deployment-oriented AI evidence because they are anchored in operational SCADA, condition-monitoring, inspection, and maintenance data. By contrast, wake-aware control, neural or operator surrogates, and layout optimization are highly relevant but more often depend on simulated flow fields, solver-in-the-loop studies, or indirect validation; they should therefore not be described with the same maturity language as operational monitoring and forecasting.

4.4. Artificial intelligence in ocean thermal energy conversion (OTEC)

Compared with other marine renewables, ocean thermal energy conversion (OTEC) remains at an early stage of technological and data maturity (Rashid et al., 2024b; Rawat and Kumar, 2024; Stamoulis et al., 2018; Xing et al., 2023). The most realistic role of AI in this domain is therefore not broad operational deployment, but support for prediction, supervisory control, and design under sparse data and strongly structured thermodynamic constraints (Rawat and Kumar, 2024; Xia et al., 2020; Zhao et al., 2024e). AI in OTEC should be interpreted as a complement to first-principles engineering rather than a replacement for it (Lou et al., 2024; Xia et al., 2020).

4.4.1. Forecasting and state estimation

OTEC remains the least mature of the four AI domains reviewed here, and that fact should be stated explicitly (Rashid et al., 2024a; Rawat and Kumar, 2024; Xing et al., 2023). The most common AI problem in OTEC is not broad field deployment but component or cycle prediction under changing thermal and hydraulic conditions (Wang et al., 2023c; Xia et al., 2020; Zhao et al., 2024e). Inputs typically include seawater temperatures, flow rates, pressures, and heat-exchanger variables; outputs include heat-transfer performance, net cycle response, or operating-state prediction (Kondeti and Palanisamy, 2025; Qi et al., 2022, 2023). Recent experimental-platform studies show that compact neural or sequence models can support heat-exchanger identification and process-state prediction, but their evidentiary role is still component-level and experimentally bounded rather than operational or fleet-scale (Liu et al., 2025b). Post-2020 physics-aware compact models are most relevant to OTEC where thermodynamic structure is strong but operating records are sparse. Hybrid thermodynamic–AI estimators or digital-twin-supported predictors can be useful for state estimation and supervisory support, but the current evidence should remain bounded as component-level or experimental-platform evidence. These studies are useful because OTEC is a strongly structured thermodynamic system with sparse real-world deployment (Lou et al., 2024; Rawat and Kumar, 2024). Their correct interpretation, however, is as experimental-scale engineering support rather than as evidence of mature operational AI (Rashid et al., 2024a; Rawat and Kumar, 2024).

4.4.2. Supervisory control

The control problem in OTEC centers on supervisory adjustment of flow rates, pumping conditions, and thermal operating points under narrow thermodynamic margins (Wang et al., 2023c; Xia et al., 2020). In principle, this is a favorable setting for hybrid or physics-aware ML because the process is governed by relatively well-understood physical relations (Lou et al., 2024; Orejarena-Rondón et al., 2023). Typical inputs include temperatures, pressures, pump states, flow rates, and related process-state variables, while the main outputs are supervisory control actions, operating setpoints, and controlled process responses (Wang et al., 2023c; Xia et al., 2020). Meaningful baselines in this literature remain rule-based supervisory logic, thermodynamic control heuristics, and experimentally tuned operating schedules (He et al., 2024; Xia et al., 2020). The most relevant performance indicators are process error, set-point tracking quality, efficiency-related gains, and agreement with experimentally observed behavior (Wang et al., 2023c; Xia et al., 2020). In practice, the contemporary literature is still dominated by small-scale platform studies and thermodynamic optimization frameworks, with validation usually limited to experimental or pilot-like conditions (Rashid et al., 2024a; Rawat and Kumar, 2024). There is therefore not yet a strong basis for claiming that advanced ML control in OTEC has reached the maturity seen in offshore-wind O&M or even wave-energy control research (Rawat and Kumar, 2024; Xia et al., 2020).

4.4.3. Design and optimization

Design and optimization are presently the most defensible AI use cases in OTEC (Xia et al., 2020; Zhao et al., 2024a). Recent studies using ANN- or LSTM-based modeling and optimization show where AI currently fits: as a compact predictor or optimizer embedded in thermodynamic design loops with experimental backstopping (Liu et al., 2025b; Xia et al., 2020; Zhao et al., 2024a). Typical metrics are prediction error, heat-exchange efficiency, net power, and secondary energy-use efficiency rather than operational reliability or fleet-scale economics (Rashid et al., 2024a; Xia et al., 2020; Zhao et al., 2024a). The caveat is obvious but important: a review should not present these results as evidence that AI in OTEC is broad, data-rich, or operationally mature (Rashid et al., 2024a; Rawat and Kumar, 2024). It is still pilot-heavy (Stamoulis et al., 2018; Xing et al., 2023).

4.4.4. Operation & Maintenance and reliability

The OTEC literature has clear prospective O&M targets—biofouling, heat-exchanger degradation, pumping-system anomalies, and cold-water-pipe integrity—but the published AI evidence remains sparse (Cao et al., 2022; Rawat and Kumar, 2024; Tang et al., 2024a). This should be treated as an identified research gap rather than expanded through unsupported speculative claims (Liang et al., 2024; Rawat and Kumar, 2024). Where AI-supported prognosis is discussed, the typical inputs are heat-exchanger signals, flow and pressure anomalies, and other subsystem monitoring variables collected under sparse pilot-scale conditions (Cao et al., 2022; Tang et al., 2024b). The corresponding outputs are usually anomaly scores, degradation indicators, and maintenance triggers rather than mature fault-taxonomy labels (Cao et al., 2022; Liang et al., 2024). Meaningful baselines remain manual process monitoring, classical process diagnostics, and first-principles engineering judgment (Lou et al., 2024; Rawat and Kumar, 2024). Validation is still largely conceptual or confined to very small-scale experimental settings, and standardized metrics are not yet well established across the OTEC AI literature (Rawat and Kumar, 2024; Tang et al., 2024b). The engineering rationale for hybrid digital-twin or physics-aware prognosis is strong because OTEC processes are structured and offshore access is costly. However, the current literature supports this as a research agenda, not as an established O&M capability (Cao et al., 2022; Tang et al., 2024b). It would be premature to imply that such systems are already well established in the sector (Liang et al., 2024; Rawat and Kumar, 2024). Table 8 intentionally preserves the thinness of the OTEC evidence base rather than masking it. The current AI literature is most defensible for state estimation, compact process prediction, supervisory support, and experimentally bounded optimization. Claims about autonomous OTEC operation, mature predictive maintenance, or deployment-grade digital twins would exceed the available evidence. For OTEC O&M, digital-twin-supported prognosis and physics-aware anomaly detection should be presented as a research agenda rather than an established capability. The engineering rationale is strong because fouling, heat-exchanger degradation, and pump anomalies are structured process problems, but long-duration field evidence and standardized failure labels are not yet sufficient.

The domain-level review above is therefore not intended as an inventory of AI methods. It establishes the evidence base for the cross-domain synthesis that follows. Across marine renewable domains, the same nominal AI method carries different engineering meaning depending on the task, data regime, baseline, and validation level. A wave forecaster trained on site-specific buoy data, a tidal controller tested in simulation, an offshore-wind anomaly detector evaluated on operational SCADA records, and an OTEC heat-exchanger surrogate validated on an experimental platform do not provide equivalent evidence. The following synthesis therefore compares AI applications by engineering defensibility rather than algorithmic breadth.

5. Post-2020 AI frontiers and engineering workflows in marine renewable energy

Classical machine-learning pipelines remain useful in marine renewable energy and should not be dismissed. ANN, SVM, RF/GB, Gaussian-process-style surrogates, and hybrid decomposition-based predictors continue to provide defensible baselines and practical tools in settings where data are tabular, site-specific, moderately sized, or strongly benchmarked. The post-2020 shift is therefore not a simple replacement of classical ML by newer architectures. Rather, it reflects a move toward methods whose inductive biases are better aligned with specific offshore engineering bottlenecks: sparse field measurements, expensive high-fidelity simulation, partial access to governing physics, wake-coupled or array-level interactions, rare-fault regimes, missing data, and unstructured maintenance information. This section therefore treats physics-informed learning, neural operators, graph learning, generative models, and LLM/VLM-enabled O&M workflows as engineering responses to task-specific constraints rather than as hype-driven labels. Their value depends on the data regime, the strength of the baseline, the realism of validation, and the task family in which they are used. Table 9 summarizes the engineering bottlenecks, domain relevance, data regimes, evidence maturity, limitations, and validation priorities associated with these post-2020 AI frontiers.

5.1. Scientific machine learning, physics-informed learning, and neural operators

Scientific machine learning has become important in marine renewable engineering because many offshore tasks are governed by known or partially known physics but constrained by limited data, costly numerical simulation, and restricted experimental coverage (Ayyad et al., 2025; Wijaya and Zhang, 2026; Zhang et al., 2025c). In such settings, purely data-driven models may interpolate well within the observed regime yet remain difficult to trust when sea states, inflow conditions, operating configurations, or structural responses move outside that regime. Physics-informed and hybrid methods matter because they incorporate governing structure directly into the learning problem, thereby addressing one of the central bottlenecks of offshore AI: the need for extrapolation, physical consistency, and data efficiency under sparse or expensive observations (Ayyad et al., 2025; Wijaya and Zhang, 2026). Neural operators extend this logic in a different direction. Rather than learning isolated input-output mappings, they approximate families of parameterized physical responses and are therefore especially relevant when many-query surrogate evaluation is needed for wake-aware prediction, design-space exploration, or control-oriented flow estimation (Lee et al., 2025; Schøler et al., 2025; Zhang et al., 2025a).

The strongest evidence for this methodological family is not uniform across domains. In wave energy, the clearest evidence lies in reduced-order system identification and constrained control, where physics-informed learning addresses the need to infer structured dynamics from limited experimental data and to support control under irregular waves. Ayyad et al. (2025) use PINNs for system identification of an oscillating surge WEC, drawing on quasi-static, free-response, and torque-forced experimental data to identify hydrostatic stiffness, radiation damping, added mass, and nonlinear damping coefficients, with validation against experimental measurements. Wijaya and Zhang (2026) integrate PINNs with non-causal MPC for rigid-body WEC control, using prior partial model information to improve sampling efficiency and testing the framework across multiple sea-wave scenarios under PTO and safe-operation constraints. In offshore wind, the strongest post-2020 evidence lies in operator-learning approaches for wake prediction, where the engineering requirement is fast, parameterized surrogate modeling of flow fields that would otherwise require repeated high-fidelity computation. ST-FNO reformulates dynamic wake prediction as a parameterized PDE-solving problem and reports accurate short- and long-horizon wake prediction with millisecond-level inference on DWM-generated data (Zhang et al., 2025c). CFNO similarly targets high-fidelity yawed far-wake prediction with a Fourier-neural-operator architecture designed for real-time digital-twin and control-oriented use (Lee et al., 2025). Graph Neural Operator work further extends this operator-learning logic by embedding turbine–turbine interaction learning into a wind-farm wake-flow surrogate (Schøler et al., 2025). These are not interchangeable use cases: in wave energy, scientific machine learning is most persuasive where physical priors support inverse modeling and control; in offshore wind, neural operators are most persuasive where many-query surrogate evaluation is the bottleneck.

The maturity boundary should remain explicit. Physics-informed learning does not eliminate identifiability problems, sensitivity to imperfect governing assumptions, or training instability under noisy boundaries (Ayyad et al., 2025; Wijaya and Zhang, 2026). Neural operators likewise should not be treated as uniformly validated across wave, tidal, offshore wind, and OTEC merely because they are promising in wake-surrogate settings. Their strongest current role is therefore methodological and task-specific: they are established as serious approaches for sparse-data system identification and constrained control in wave energy, and for wake-oriented surrogate prediction in offshore wind, but they remain far from uniformly mature across all marine renewable applications (Ayyad et al., 2025; Lee et al., 2025; Schøler et al., 2025; Zhang et al., 2025c). For tidal systems and OTEC, scientific-ML relevance is technically plausible and, in some cases, highly attractive, yet the present evidence base is still too limited to support broad claims of deployment readiness.

5.2. Graph learning for wake-coupled farms and interaction-rich arrays

Graph learning is important because it changes the representation of the engineering system itself. In farms and arrays, the relevant units are not independent samples; they are interacting devices whose inflows, outputs, fatigue exposure, and surrounding flow fields depend on one another. That relational structure is central in offshore wind and conceptually extends to tidal arrays and wave farms. Graph-based models therefore matter not as another generic deep-learning architecture, but because they provide an inductive bias that is aligned with coupled-system physics (Duthé et al., 2023; Qiu et al., 2024; Schøler et al., 2025). This directly addresses a key offshore bottleneck: single-device models often fail to represent wake directionality, neighborhood influence, nonlocal coupling, and layout dependence with sufficient fidelity for farm-level analysis (Duthé et al., 2023; Qiu et al., 2024; Xiao et al., 2026).

The strongest evidence currently lies in offshore wind. Recent work shows graph learning being used for real-data forecasting, wake-aware surrogate modeling, and joint estimation of power, turbulence, and load-related quantities. Duthé et al. (2023) use GNNs with PyWake to estimate rotor-averaged wind speed, turbulence intensity, power production, and damage equivalent loads for wake-affected turbines across arbitrary wind-farm layouts. Qiu et al. (2024) propose a temporal-spatial graph neural network for wind-power forecasting that combines temporal modules with graph convolution and explicitly accounts for blockage effects; the model is validated on a real-world SCADA dataset from a 134-turbine wind farm with 10-min records over 245 days. Schøler et al. (2025) propose a Graph Neural Operator for wind-farm wake flow, using graph layers to encode turbine–turbine interactions and predict wind speed at target locations in simulated wind-farm layouts. More recent offshore-wind cluster forecasting work extends the same logic through an ASTGCN framework in which graph construction and loss-function selection co-evolve to capture dynamic wind-speed propagation and spatiotemporal coupling across wind-farm groups (Xiao et al., 2026). In this context, graph structure is not decorative; it encodes the physical influence network among turbines and improves representation of farm-scale interactions that are difficult to capture with isolated-device models. This is especially important for wind-power forecasting and wake-aware prediction, where adjacency defined by wake, blockage, or learned influence is more meaningful than purely geometric neighborhood definitions (Duthé et al., 2023; Qiu et al., 2024; Xiao et al., 2026).

The maturity boundary, however, remains narrow. The same relational logic is clearly relevant to tidal arrays and wave farms, where hydrodynamic interaction is also central, but direct published evidence is much less dense. For thermal systems and OTEC, the case is thinner still. Graph learning should therefore be treated as already important in the analytical vocabulary of the field, but operational maturity remains concentrated in offshore wind and largely in forecasting and surrogate-model settings rather than in fully field-validated closed-loop farm control (Duthé et al., 2023; Qiu et al., 2024; Schøler et al., 2025). The most defensible interpretation is that graph learning is established as a major offshore-wind methodological direction and methodologically promising for broader marine-array problems, but not yet evidenced symmetrically across all marine renewable domains.

5.3. Generative models for rare faults, missingness, imbalance, imputation, and anomaly-sensitive monitoring

Generative modeling has become relevant to offshore engineering because many monitoring and maintenance settings are defined by rare faults, missing or incomplete telemetry, severe class imbalance, and the need to distinguish genuinely abnormal behavior from normal operational variability (Habbouche et al., 2024; Yao et al., 2024, 2025). In such conditions, the main value of generative methods is not generic data synthesis for its own sake, but the ability to learn structured representations of normality, support anomaly-sensitive monitoring, assist imputation or reconstruction under incomplete data, and improve modeling in sparse-label regimes. This addresses a bottleneck that is pervasive in marine renewable O&M: the statistical structure of the problem is often dominated by scarcity and imbalance rather than by abundant fault labels (Yao et al., 2024, 2025).

The strongest established evidence again lies in offshore wind. Diffusion-based and related generative approaches are now being used in condition-monitoring settings where SCADA data are available and abnormal-state detection can be evaluated against operationally meaningful events. Yao et al. (2025) propose a conditional stochastic process diffusion model for wind-turbine condition monitoring and fault identification, using SCADA datasets from two real wind farms, KL-divergence-based anomaly evaluation, and multivariate coefficient-of-variation analysis to identify abnormal states and fault locations. A subsequent diffusion-based study introduces a dynamic fusion conditional diffusion model with physical-information dynamic fusion and SHAP-value analysis, again targeting anomaly detection and fault identification from real wind-farm data (Yao et al., 2025). In this setting, generative models are most persuasive when they support anomaly detection, fault localization, or uncertainty-sensitive monitoring rather than when they are presented simply as data generators. A second, more tentative but relevant line of evidence appears in tidal applications, where GAN-assisted augmentation has entered biofouling-detection pipelines because the underlying image regime is small, noisy, and highly imbalanced (Habbouche et al., 2024). These examples show that generative methods are no longer conceptually marginal in marine-energy AI, but their strongest current role is concentrated in monitoring tasks where imbalance, missingness, and latent-structure learning matter more than pointwise prediction alone.

The maturity boundary must nevertheless remain tight. The strongest support is still concentrated in offshore-wind condition monitoring; adjacent uses such as imputation, synthetic augmentation, or uncertainty-aware reconstruction remain promising but less mature. Synthetic or reconstructed outputs should not be assumed to preserve the operational physics of failure merely because they improve anomaly separability on curated datasets (Yao et al., 2024, 2025). Nor should offshore-wind-heavy evidence be generalized to the field as a whole. For wave systems, tidal devices, and especially OTEC, the engineering relevance of generative methods is plausible in sparse-label and anomaly-sensitive settings, but the evidence remains fragmentary. The appropriate conclusion is therefore bounded: generative models are now practically relevant for imbalance-sensitive O&M and incomplete telemetry, yet their deployment maturity remains selective rather than field-wide (Habbouche et al., 2024; Yao et al., 2024, 2025).

5.4. LLM/VLM-enabled O&M and inspection workflows

The post-2020 shift in marine-energy AI is not only numerical; it is also informational. Offshore operations and maintenance generate large volumes of data that do not fit neatly into classical sensor-to-label pipelines, including free-text maintenance logs, work orders, heterogeneous inspection notes, and image-heavy inspection archives (Malyi et al., 2026; Tan and Carroll, 2025; Zhang et al., 2025a; Zhou et al., 2025). Large language models and vision-language models matter because they target this unstructured layer of offshore information. They therefore address an engineering bottleneck that traditional predictive models do not solve well: extracting operationally useful structure from text and image data that are expensive to label, semantically inconsistent, and often incomplete. Their primary relevance is in workflow support, knowledge organization, maintenance-log interpretation, and data-efficient inspection assistance (Malyi et al., 2026; Zhang et al., 2025f; Zhou et al., 2025).

The strongest current evidence lies in offshore-wind O&M. On the language side, LLMs are being evaluated for maintenance-log labeling, knowledge extraction, and support for failure-analysis workflows. Malyi et al. (2026) benchmark proprietary and open-source LLMs for classifying unstructured wind-turbine maintenance logs and conclude that the most responsible near-term use is human-in-the-loop labeling support rather than fully autonomous classification. Tan and Carroll (2025) examine LLMs for wind-turbine gearbox failure prediction by prompting GPT-4o and DeepSeek-V3 to generate machine-learning pipelines for a labeled SCADA-based gearbox-condition classification task and comparing these pipelines with baseline ML models. On the vision side, VLM-based approaches are emerging for blade inspection and defect reasoning, especially where conventional supervised vision is bottlenecked by small, shifting, or weakly labeled defect datasets. Zhang et al. (2025f) propose a RAG-grounded VLM framework for zero-shot wind-turbine blade inspection using a multimodal knowledge base of technical documentation, reference images, and domain-specific guidelines, evaluated on a small labeled blade-image dataset. Zhou et al. (2025) similarly develop a few-shot visual reasoning pipeline that integrates visual-text RAG with a pre-trained VLM to reason about wind-turbine blade damage type and severity without task-specific fine-tuning. These developments matter because offshore O&M is costly, text-rich, image-rich, and operationally heterogeneous. In that setting, LLM/VLM systems can add value even when they are not the final decision maker, because they can reduce the burden of log standardization, accelerate information retrieval, and support inspection interpretation under sparse labeled data.

The maturity boundary should be stated without ambiguity. The present evidence supports these systems as human-in-the-loop support tools, not as autonomous maintenance agents (Malyi et al., 2026; Tan and Carroll, 2025). Performance remains sensitive to calibration, retrieval grounding, test-set scale, and the semantic structure of the underlying records. In vision-language workflows, small and curated evaluation sets still limit the strength of generalization claims; in language workflows, imperfect consistency in maintenance records constrains reliability (Malyi et al., 2026; Zhang et al., 2025f; Zhou et al., 2025). The most defensible interpretation is therefore that LLM/VLM-enabled O&M has emerged as a real and substantively important subfield, strongest at present in offshore-wind workflow assistance, log labeling, knowledge retrieval, and inspection support, while broader claims of autonomous diagnosis or cross-domain operational maturity would be premature. For tidal systems, wave energy, and OTEC, relevance is technically plausible but current evidence remains limited.

Taken together, these post-2020 methodological shifts do not simply

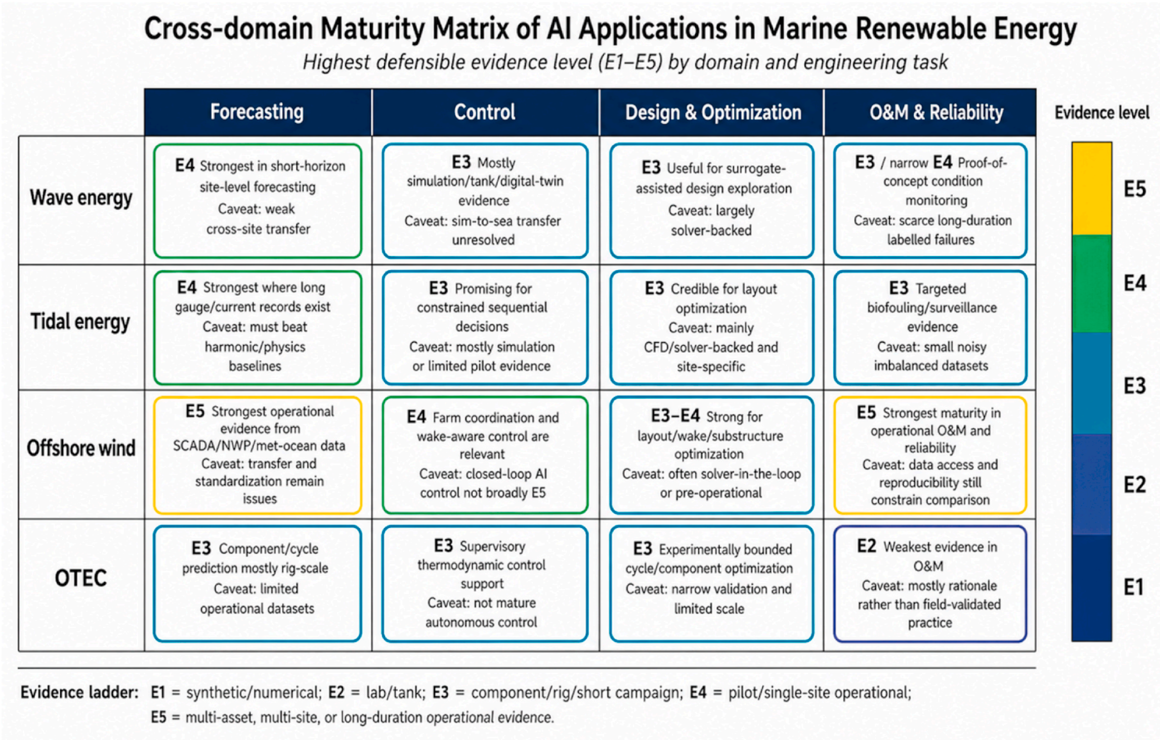

Fig. 1. Cross-domain maturity matrix of AI applications in marine renewable energy.

append several new algorithm names to an older literature. They reorganize the field around four structurally important offshore bottlenecks: physical constraint under data scarcity, coupled-system dependence across farms and arrays, imbalance-sensitive monitoring under rare faults and missingness, and the operational value of unstructured text and image data in O&M (Ayyad et al., 2025; Malyi et al., 2026; Qiu et al., 2024; Wijaya and Zhang, 2026; Yao et al., 2024). Their evidentiary maturity remains uneven, with the strongest current concentration in offshore wind and a more selective foothold in wave-energy scientific machine learning. A modern review must therefore treat these directions as central methodological themes while preserving the distinctions between plausible relevance, emerging evidence, and established deployment-oriented support.

6. Cross-domain comparison and synthesis

The domain-level review above should be read as the evidence base for a cross-domain engineering synthesis rather than as an inventory of AI applications. The same nominal model family can carry different engineering meaning depending on the task, data regime, baseline, validation level, and deployment context. A wave-energy controller tested in a numerical tank, a tidal-current forecaster evaluated against harmonic baselines, an offshore-wind anomaly detector trained on operational SCADA records, and an OTEC heat-exchanger surrogate validated on an experimental platform do not provide equivalent evidence. This section therefore synthesizes the literature by engineering defensibility: which AI roles are currently credible, which remain conditional on E1–E3 validation, which have stronger E4–E5 operational support, and which deployment claims should be avoided.

6.1. Evidence maturity across domains: why AI readiness is uneven

The clearest cross-domain finding is that AI maturity in marine renewable energy is uneven. Offshore wind currently provides the strongest deployment-oriented evidence because the sector combines industrial maturity with dense operational data. Utility-scale offshore wind farms generate SCADA records, condition-monitoring and vibration streams, inspection imagery, alarms, maintenance logs, and met-ocean or NWP-linked data. These data sources support more realistic E4–E5 evaluation, especially in operational forecasting and O&M/reliability.

Wave and tidal energy show technically meaningful AI progress, but their evidence bases are more frequently bounded by E1–E3 validation. In wave energy, forecasting benefits from buoy archives, hindcasts, and site-level measurements, but control, design optimization, and O&M still rely heavily on simulation, tank, laboratory, digital-twin, short-campaign, or sparse offshore datasets. In tidal energy, long gauge and current records support useful forecasting studies, but control, array design, biofouling surveillance, and underwater inspection remain fragmented across site-specific campaigns, numerical models, and limited labels. OTEC is the least mature AI domain, with evidence concentrated mainly in component-level prediction, rig-scale or experimental-platform studies, supervisory support, and thermodynamic or simulation-based optimization.

This imbalance is not a weakness of the review structure; it is one of the review's findings. The manuscript is evidence-weighted rather than page-balanced. Offshore wind receives deeper treatment because the available AI literature is denser and more operationally validated. Shorter or more cautious treatment of wave, tidal, and OTEC does not imply lower engineering importance; it reflects thinner AI evidence, lower dataset availability, and less mature validation. This evidence-weighted interpretation is essential for avoiding false equivalence between algorithmic promise and operational readiness.

6.2. Task-family comparison: forecasting, control, design optimization, and O&M

Forecasting is the most mature task family across the review, but maturity differs sharply by domain. Offshore wind forecasting has the strongest evidence because operational SCADA, met-ocean records, NWP-linked data, and farm-level monitoring allow evaluation under realistic operating conditions. Wave forecasting is also relatively defensible for site-specific short-horizon use, especially where buoy records, hindcasts, and physical forecast correction are available, but cross-site transfer and storm-regime robustness remain weaker. Tidal forecasting is different because tidal dynamics are partly predictable by physics; AI should therefore be judged by whether it adds value beyond harmonic and physical baselines under local disturbance, not merely by whether it outperforms another black-box model. OTEC forecasting and state estimation remain component- or process-level, with evidence concentrated in experimental or pilot-like settings.

Control is strategically important but less mature. Wave and tidal control problems are sequential, constrained, and physically structured, making RL-based control, MPC with learned surrogates, adaptive control, and physics-informed control support attractive. However, much of the evidence remains E1–E3, and simulation or tank validation should not be interpreted as deployment readiness. Offshore-wind farm coordination has stronger industrial relevance, especially for wake-aware control and graph/operator-assisted coordination, but many AI-driven control studies still rely on simulated wake fields, surrogate evaluations, or indirect validation. OTEC supervisory control remains experimentally bounded and should be interpreted as compact process-support evidence rather than mature autonomous control.

Design and optimization are methodologically active across all four domains because marine-energy design evaluations are expensive. The most defensible AI role here is not replacing physics, but accelerating design-space exploration through surrogate models coupled with optimization frameworks. In wave and tidal systems, surrogate-assisted design can reduce the burden of hydrodynamic or CFD-informed search, but surrogate error, constraint feasibility, and uncertainty propagation must be reported. In offshore wind, layout optimization, wake-loss reduction, cable routing, and LCOE-oriented design are highly relevant, yet the evidence often remains solver-in-the-loop or pre-operational. In OTEC, optimization is best interpreted as thermodynamic or experimental decision support rather than sector-wide deployment evidence.

O&M and reliability show the strongest domain separation. Offshore wind is the clear leader because its operational assets generate SCADA, CMS/vibration, alarms, inspection imagery, and maintenance records. These data enable anomaly detection, normal-behavior modeling, log analysis, inspection triage, lead-time estimation, and maintenance decision support under E4–E5 conditions. Wave O&M remains much weaker because long-duration failure-labeled offshore data are scarce. Tidal O&M has a narrower but meaningful niche in biofouling surveillance and underwater inspection, where image quality, class imbalance, turbidity, and uncertain labels constrain generalization. OTEC O&M is still best treated as a research agenda around physics-aware prognosis and digital-twin-supported monitoring rather than an established AI subfield.

6.3. Method-selection guidance: when classical ML is sufficient and when frontier AI is justified

The evidence does not support a simple hierarchy in which newer AI methods are always preferable to classical machine learning. ANN, SVM/kernel models, RF/GB/XGBoost, Gaussian-process-style surrogates, and hybrid decomposition-based predictors remain appropriate when the engineering task is well bounded, the data are tabular or moderately sized, the operating regime is narrow, and meaningful baselines exist. In many forecasting, classification, and surrogate-design tasks, these methods provide useful reference points and should remain part of the benchmark set.

Frontier methods are justified when they address an engineering bottleneck that classical pipelines do not handle well. Physics-informed learning and PINNs are most defensible when the system is governed by known or partially known physics but field data are sparse, expensive, noisy, or incomplete. Their value lies in improving physical consistency, data efficiency, constrained system identification, and extrapolation discipline. They should not be interpreted as eliminating the need for physical testing, tank validation, or field validation.

Neural operators and operator-learning approaches are justified when repeated evaluation of parameterized physical responses is the bottleneck. Their strongest current relevance is in many-query surrogate evaluation, such as wake-field approximation, control-oriented flow estimation, or fast design-space exploration. Their maturity should be distinguished from operational deployment: a solver-trained neural operator can be valuable for surrogate acceleration without yet supporting claims of field-tested autonomous control.

Graph learning is justified when the engineering system is relational. Offshore wind farms, tidal arrays, wave farms, and sensor networks involve nonlocal interactions, wake directionality, layout dependence, and shared environmental forcing. In these settings, graph-based models can represent turbine–turbine, device–device, or sensor–asset relationships more naturally than independent-device models. However, graph learning should not be used merely because a system has multiple assets. The graph structure must be physically meaningful and validated under layout, inflow, or site changes.

Generative and diffusion-based models are most relevant where the data regime is dominated by rare faults, class imbalance, missing telemetry, incomplete inspection imagery, or weak labels. Their defensible role is to support anomaly-sensitive monitoring, imputation, reconstruction, or selective augmentation. The main validation risk is that synthetic or reconstructed data may improve offline metrics without preserving operational failure physics. These models therefore require downstream validation against real events, maintenance outcomes, false-alarm burden, and distribution-shift robustness.

Foundation models, including LLMs and VLMs, should be treated as human-in-the-loop workflow support rather than autonomous offshore decision-makers. Their realistic role is to organize, retrieve, summarize, and cross-reference maintenance logs, inspection imagery, work orders, and historical operating context under expert supervision. They may support triage and evidence review, but they require grounding, provenance tracking, abstention, uncertainty awareness, and human oversight. Claims of fully autonomous maintenance diagnosis, unsupervised operational decisions, or offshore “intelligence” should be avoided.

6.4. Engineering decision implications and deployment boundaries

The engineering implication of the cross-domain comparison is that AI claims should be bounded by task family and evidence level. Offshore-wind forecasting and O&M provide the strongest basis for deployment-oriented claims because they are supported by richer operational datasets and more E4–E5 evidence. Wave and tidal forecasting are credible but more site-specific, while their control, design, and O&M applications remain more frequently E1–E3 and should be interpreted as constrained proof of concept, design acceleration, or targeted monitoring support. OTEC remains the least mature domain, with defensible AI use concentrated in state/component prediction, supervisory support, and experimentally bounded optimization.

This boundary also determines which claims should be avoided. First, E1–E2 studies should not be used to claim broad deployment readiness. Second, simulation-based control studies should not be compared directly with operational O&M studies. Third, methodological novelty should not be treated as equivalent to engineering maturity. Fourth, offshore-wind maturity should not be generalized automatically to wave, tidal, or OTEC systems. Fifth, OTEC AI should not be described as operationally mature when the evidence remains sparse, component-level, rig-scale, or experimental.

Fig. 1 summarizes the evidence-weighted maturity pattern that emerges from the cross-domain synthesis. It should be read as a map of current AI evidence density across task families, not as a ranking of the intrinsic engineering importance of the four marine renewable technologies.

The matrix summarizes the highest defensible evidence level across four engineering task families—forecasting, control, design and optimization, and O&M/reliability—for wave energy, tidal energy, offshore wind, and OTEC. Evidence levels follow the E1–E5 ladder used in this review: E1 = synthetic/numerical validation; E2 = laboratory/tank validation; E3 = component, rig, or short-campaign validation; E4 = pilot or single-site operational validation; and E5 = multi-asset, multi-site, or long-duration operational evidence. The figure is intended as a synthesis of evidence maturity rather than a ranking of technology importance.

The maturity matrix reinforces three practical conclusions. First, offshore wind is the current benchmark for deployment-oriented marine-energy AI because forecasting and O&M are supported by operational datasets and higher evidence levels. Second, wave and tidal energy contain important AI opportunities, but the strongest claims remain task-specific: forecasting is comparatively more defensible, while control, design, and O&M require stronger transfer and field validation. Third, OTEC remains emerging, and its AI applications should be interpreted as process-support, state-estimation, supervisory, or experimentally bounded optimization tools rather than mature operational systems.

6.5. *Transferability, benchmarking, and validation priorities*

The main barrier to stronger cross-domain AI maturity is not a lack of algorithms but a lack of comparable validation. Table 4 showed that each domain has different data sources, baselines, metrics, label structures, and evidence ceilings. Therefore, the next stage of marine-energy AI should prioritize benchmarking practices that preserve domain specificity while making claims comparable. Forecasting should report horizon-specific performance against persistence, harmonic, physical, or NWP baselines. Control should report energy capture, constraint violations, structural loading, latency, and robustness rather than only reward or simulated gain. Design studies should report surrogate error, constraint feasibility, and sensitivity of techno-economic conclusions. O&M studies should report false-alarm burden, lead time, event-level detection, maintenance utility, and robustness under drift.

Transferability is the decisive test for many claims. Cross-site and cross-farm validation are especially important in offshore wind, where rich data can still be proprietary, heterogeneous, or drift-prone. Wave and tidal studies require stronger tests across wave climates, bathymetry, turbine/array configurations, and environmental regimes. OTEC studies require longer experimental and pilot records, independent physical measurements, and clearer separation between thermodynamic-model validation and operational validation. Without these steps, apparent gains may remain tied to dataset convenience rather than engineering reliability.

The strongest research priorities are therefore field-duration datasets, transparent or semi-open benchmark infrastructures, transfer-aware evaluation, uncertainty calibration, and certification-aware validation. These priorities matter more than adding further algorithmic variety. The review's central synthesis is that AI has become technically valuable in marine renewable energy, but engineering readiness is uneven and must be judged through the joint lens of task family, data regime, baseline strength, and evidence level.

7. Challenges and limitations of artificial intelligence

Artificial intelligence in marine renewable energy should be evaluated against the constraints of offshore engineering rather than against benchmark performance alone. Across wave, tidal, offshore wind, and ocean thermal energy conversion (OTEC), the central limitations are not reducible to generic statements about “data quality” or “model interpretability.” They arise from identifiable mismatches between engineering tasks, data regimes, model assumptions, and validation depth. In this review, the principal limitations are organized around five method-relevant bottlenecks: validation weakness and domain shift;

Table 10
Strategic future research directions for AI in marine renewable energy.

Time horizon	Direction cluster	Marine-energy rationale	Main research need	Current status
Short-term	Benchmark creation	Comparability remains weak across forecasting, control, design, and O&M tasks	Task-specific baselines, metrics, and validation protocols	High priority
Short-term	Open/semi-open data infrastructures	Proprietary and fragmented datasets limit reproducibility and cumulative evidence	Shared metadata, taxonomies, benchmark partitions, and reporting templates	High priority
Short-term	Physics-informed/hybrid learning	Sparse field data and extrapolation needs are common in wave, tidal, and OTEC applications	Physically constrained learning under limited-data conditions	Actionable
Short-term	Graph learning	Wake-coupled farms and interaction-rich arrays are not well represented by independent-device models	Relational modeling with physically meaningful graph structure	Actionable, strongest in offshore wind
Short-term	LLM/VLM-driven O&M and inspection	Offshore maintenance increasingly depends on text, logs, and imagery, not sensors alone	Grounded, auditable, human-in-the-loop workflows	Actionable in limited settings
Long-term	Neural operators	Many-query surrogate prediction is needed for wake modeling and fast design/control evaluation	Stable operator learning across varying offshore conditions	Emerging
Long-term	Generative models	Rare faults, class imbalance, and missingness remain central in offshore monitoring	Distribution-aware anomaly detection, imputation, and selective augmentation	Emerging
Long-term	Graph learning beyond offshore wind	Wave farms and tidal arrays are also interaction-rich but still weakly evidenced	Array-scale validation under sparse deployment data	Exploratory
Long-term	Multimodal LLM/VLM maintenance copilots	Offshore decision support may require integrated use of text, images, and operating context	Provenance, retrieval grounding, auditability, and calibrated oversight	Exploratory
Long-term	Integrated benchmarked ecosystems	Progress will remain fragmented unless models, datasets, and validation frameworks co-evolve	Linked infrastructure for cumulative, cross-study evidence	Strategic long-term goal

rare-fault, imbalanced, and incomplete monitoring data; coupled-system dependence; sparse-data extrapolation under strong physics; and trust, provenance, and auditability in emerging multimodal O&M systems. This framing is more useful than a generic digitalization narrative because it shows why particular method families have become attractive, while also clarifying why those same methods remain constrained in practice.

7.1. Validation weakness, domain shift, and transfer limits

The most pervasive limitation across the literature is not lack of model sophistication, but lack of sufficiently strong validation. Many reported gains still arise under E1–E3 conditions: numerical studies, laboratory or basin experiments, short field campaigns, and bounded pilot settings (Alcibar et al., 2025; Badoe et al., 2022; Chen et al., 2024a). This matters because offshore systems are exposed to storms, biofouling, corrosion, sensor drift, maintenance interventions, and gradual asset aging, all of which alter the data-generating process after deployment (Groun et al., 2023; Li and Choung, 2017; Qian et al., 2022). A model that performs well under nominal or narrow conditions may fail once sea state, turbulence regime, operating envelope, or subsystem condition moves beyond the training distribution (Covarrubias-Contreras et al., 2025). In this sense, domain shift is not a secondary nuisance; it is a defining feature of marine-energy AI.

This limitation is distributed unevenly across the four domains. Offshore wind has the richest operational evidence and the highest share of E4–E5 studies, particularly in forecasting and O&M (Bashir et al., 2022; Díaz and Soares, 2020; Kisvari et al., 2021), but even here cross-farm transfer remains difficult because atmospheric conditions, SCADA conventions, sensor layouts, and maintenance taxonomies differ materially across sites (Kisvari et al., 2021). Wave and tidal systems are more often evaluated in site-specific or pre-deployment settings, especially for control and design, so claims of generality should remain restrained even when reported gains are technically meaningful (Qian et al., 2022). OTEC remains the least mature in validation terms, with much of the evidence concentrated in experimental or rig-scale settings (Kondeti and Palanisamy, 2025; Rawat and Kumar, 2024; Xia et al., 2020). As a result, validation weakness is not merely a methodological inconvenience; it is the principal reason that performance claims cannot be interpreted symmetrically across domains.

This validation problem also constrains method choice. Data-hungry deep models, reinforcement-learning controllers, and multimodal inspection systems may appear attractive, but their practical credibility depends on cross-regime robustness, calibrated uncertainty, and evidence that extends beyond curated datasets or simulation-heavy case studies (Tang et al., 2024a; Zhang et al., 2025f). The field therefore remains limited less by the availability of algorithms than by the relative scarcity of certification-grade evidence under realistic operational shift (Alcibar et al., 2025; Rajaoarisoa et al., 2025).

7.2. Class imbalance, rare-fault regimes, and missingness in monitoring data

A second major bottleneck is the statistical structure of O&M and reliability data. In many offshore settings, failures are rare, labels are incomplete, and the observed distribution is dominated by healthy or near-normal operation (Ashrafi Niaki et al., 2023; Bao et al., 2024; Kisvari et al., 2021). Missingness is also pervasive: sensors fail, communications degrade, records are truncated, maintenance logs are inconsistently completed, and not all anomalies are confirmed by inspection (Baek et al., 2023; den Bieman et al., 2023; Sarkar et al., 2019). These properties make conventional supervised classification intrinsically difficult. High nominal accuracy may coexist with poor sensitivity to rare but operationally consequential faults, while models trained on curated or balanced datasets may provide a misleading impression of field readiness.

This is precisely why generative and distribution-aware methods have become methodologically relevant. Their value is not simply in synthetic data production, but in learning the structure of normal behavior, improving anomaly sensitivity under weak labels, handling incomplete telemetry, and supporting imbalance-aware monitoring (Yao et al., 2024, 2025). In offshore wind, where SCADA-based condition monitoring is most mature, rare-fault regimes and missingness create a clear rationale for diffusion-based and related generative approaches (Yao et al., 2024, 2025). In tidal monitoring, GAN-assisted augmentation has emerged because underwater imagery is small, noisy, and imbalanced (Habbouche et al., 2024). However, the rationale for these methods should not be confused with proof of maturity. A model that improves anomaly separation or imputation on a curated dataset does not automatically preserve the physics of failure, nor does it guarantee robustness under changing operating conditions.

The constraint is particularly severe outside offshore wind. Wave O&M remains limited by sparse offshore failure labels and short-duration monitoring records (Bao et al., 2024; Freeman et al., 2021). Tidal O&M is often further complicated by underwater visibility, class imbalance, and weak labels in biofouling or anomaly-detection workflows (Habbouche et al., 2024). OTEC has even less mature fault evidence, so the attraction of anomaly-aware or generative monitoring is conceptually strong but empirically underdeveloped (Cao et al., 2022; Rawat and Kumar, 2024). The appropriate conclusion is therefore careful: rare-fault, imbalanced, and incomplete data create a genuine rationale for generative or distribution-aware methods, but current evidence still supports selective use rather than broad deployment claims.

7.3. Coupled-system dependence and interaction networks

A third limitation concerns the representation of offshore systems as if they were collections of independent units when, in reality, many of the relevant engineering problems are interaction-rich. Wind farms are shaped by wake propagation and blockage (Duthé et al., 2023; Qiu et al., 2024); tidal arrays exhibit hydrodynamic interaction (Fituri et al., 2020; Qian et al., 2022); wave farms and shared-platform concepts introduce coupled mechanical and environmental responses (Geng et al., 2023; Hallak and Guedes Soares, 2025). In these settings, independent-device predictors or controllers may perform adequately for narrow local tasks but are structurally misaligned with the engineering system when the objective is farm-level forecasting, coordinated control, or array-aware design.

This is the methodological rationale for graph learning and related relational models. Graph-based methods matter because they encode dependence structure directly rather than treating interaction as noise or as an afterthought (Duthé et al., 2023; Qiu et al., 2024; Schøler et al., 2025). Their strongest current evidence lies in offshore wind, where wake-coupled farms provide both the data regime and the engineering need for relational modeling (Qiu et al., 2024; Xiao et al., 2026). Yet the limitation here is twofold. First, the strongest graph-learning evidence remains concentrated in offshore-wind forecasting and surrogate modeling rather than in field-validated closed-loop control (Duthé et al., 2023; Schøler et al., 2025). Second, although the same inductive logic is highly plausible for tidal arrays and wave farms, the published evidence base in those domains remains much thinner (Fituri et al., 2020; Qian et al., 2022). Accordingly, the existence of coupled-system dependence strongly motivates graph learning, but the maturity of graph-based deployment remains domain- and task-specific rather than general across marine renewables.

The broader limitation is therefore not simply “lack of graph methods,” but the persistence of model-form mismatch between the structure of the engineering system and the structure assumed by the learning model. Where interaction matters and remains unmodeled, reported gains may be fragile, local, or misleadingly optimistic.

7.4. Data scarcity, extrapolation, and the case for physics-informed or hybrid models

A fourth limitation is the combination of sparse data and extrapolation demand. This problem is especially acute in wave energy, tidal design and control, and OTEC, where long-duration operational datasets are limited and much of the evidence remains numerical, experimental, or pilot-scale (Bradbury and Conley, 2021; Chen et al., 2024a; Luppichini et al., 2025). In such settings, purely black-box learning is often poorly matched to the engineering requirement (Ayyad et al., 2025; Wijaya and Zhang, 2026). Offshore systems must operate beyond the narrow conditions represented in the training data, and many of the most important decisions—control under abnormal seas, structural response under rare conditions, thermal performance under changing process states—depend on behavior outside a well-sampled regime.

This limitation explains the attraction of physics-informed and hybrid models. These approaches are motivated not by novelty alone, but by the need to embed governing structure, regularize learning under sparse observations, and constrain extrapolation in ways that remain physically interpretable (Ayyad et al., 2025; Wijaya and Zhang, 2026; Zhao et al., 2024d). They are particularly relevant when solver knowledge exists but field data are scarce, or when compact experimental datasets must support control or prediction under conditions not densely observed in practice. However, the existence of that rationale should not be overstated into claims of solved trustworthiness. Physics-informed learning does not remove identifiability problems, model-form error, or sensitivity to imperfect boundary conditions (Halicki et al., 2025; Yuan et al., 2015). Hybrid models may improve data efficiency while still inheriting bias from both the learned and the physics-based components. In OTEC especially, the attractiveness of hybrid methods follows directly from process structure and data scarcity, yet the evidence base remains too limited to justify strong operational claims (Rawat and Kumar, 2024; Xia et al., 2020).

Across the four domains, the central constraint is therefore not merely scarcity of data, but scarcity of the right kind of data for extrapolative engineering use. Physics-informed and hybrid models are the most methodologically plausible response in such conditions, but they remain bounded by validation weakness and by the difficulty of proving robust generalization in open-water environments.

7.5. Trust, explainability, provenance, and human oversight in LLM/VLM-assisted O&M

A fifth and increasingly important limitation concerns LLM/VLM-assisted O&M systems. These models are attractive because offshore maintenance is no longer dominated by continuous sensor streams alone; it also depends on free-text logs, work orders, inspection reports, images, and video (Malyi et al., 2026; Tan and Carroll, 2025). In this setting, LLMs and VLMs can help structure information, retrieve relevant records, support defect interpretation, and reduce labeling burden (Zhang et al., 2025f; Zhou et al., 2025). Yet their use raises a distinct set of limitations that are not adequately captured by generic calls for "interpretability." The central issues are trust, provenance, auditability, hallucination risk, retrieval dependence, and the continuing need for human oversight (Malyi et al., 2026; Zhou et al., 2025).

These concerns are especially acute because the downstream decisions are operational rather than merely informational. A maintenance-log label, a defect interpretation, or a severity assessment may affect work planning, safety margins, or component replacement decisions (Malyi et al., 2026; Tan and Carroll, 2025). For that reason, provenance matters: operators must know whether a conclusion was grounded in retrieved maintenance evidence, inferred from incomplete context, or generated by a model without domain-verified support. Auditability is equally important: a workflow that cannot be traced, reviewed, and challenged is difficult to justify in cost-critical or safety-critical settings. Hallucination risk, while often discussed abstractly, has a concrete operational meaning here: a plausible but unsupported failure narrative or inspection interpretation may be more dangerous than a model that simply abstains.

These limitations explain why the most defensible current role of LLM/VLM systems is human-in-the-loop support, not autonomous diagnosis or autonomous maintenance decision-making (Malyi et al., 2026; Zhang et al., 2025f; Zhou et al., 2025). This boundary should be made explicit. Offshore wind currently provides the strongest evidence because it has the richest mixture of logs, imagery, and operational workflows, but even there the field is still emerging and sensitive to retrieval quality, semantic inconsistency in logs, and narrow evaluation sets (Malyi et al., 2026; Tan and Carroll, 2025; Zhou et al., 2025). For wave, tidal, and OTEC, the relevance of these systems is plausible, but the evidence is much thinner. LLM/VLM-assisted O&M is methodologically important, but its present limitation is not only model accuracy; it is the unresolved requirement for grounded, auditable, and overseen operational use.

7.6. Synthesis

Taken together, these limitations show that the main barriers to AI deployment in marine renewable energy are not captured by a generic contrast between "traditional methods" and "advanced AI." The field is constrained by rare-fault data structures, interaction-rich system behavior, sparse-data extrapolation, weak validation under domain shift, and the trust requirements of multimodal operational workflows. These are precisely the conditions that motivate generative models, graph learning, physics-informed or hybrid methods, and carefully bounded LLM/VLM assistance. At the same time, the rationale for using these method families should not be confused with evidence that they are already mature across all four marine domains (Ayyad et al., 2025; Qiu et al., 2024; Yao et al., 2024). Offshore wind presently has the strongest basis for operational inference; wave and tidal remain more often site-specific or pre-deployment; and OTEC remains the least mature (Badoe et al., 2022; Bashir et al., 2022; Rawat and Kumar, 2024). The methodological implication is therefore disciplined rather than expansive: future advances will depend less on adding more algorithm names and more on building validation depth, transfer-aware evaluation, grounded multimodal workflows, and model choices that are structurally aligned with offshore engineering constraints.

8. Future research directions

Future research in marine renewable energy AI should be guided less by algorithm novelty in the abstract and more by the specific engineering constraints that continue to limit deployment: sparse field evidence, heterogeneous and often proprietary data regimes, weak comparability across studies, coupled-system dependence, rare-fault monitoring conditions, and the need for grounded operational support. For that reason, a useful agenda is not a generic digitalization program but a structured progression from near-term actionable priorities to longer-term emerging directions. The distinction matters. Some directions can be pursued immediately with current engineering workflows and data constraints, whereas others remain more exploratory because they require stronger validation, broader infrastructure, or methodological stabilization before they can support dependable offshore decisions. The resulting short- and long-term research priorities are summarized in Table 10.

8.1. Short-term actionable priorities

8.1.1. Benchmark creation and evaluation discipline

The most immediate priority is the creation of task-specific benchmarks that reflect the actual structure of marine renewable engineering problems rather than generic machine-learning comparisons. The literature still suffers from inconsistent baselines, varying forecast horizons, incomparable sampling regimes, and uneven reporting of validation context. In forecasting, this means benchmark suites that include physically meaningful baselines such as persistence, harmonic analysis, numerical wave/current models, or NWP-derived references where appropriate. In control, benchmarks should include constraint violations, absorbed energy, fatigue or load penalties, and latency rather than predictive accuracy alone. In design and optimization, surrogate error relative to the underlying solver, constraint feasibility, and uncertainty propagation should be reported routinely. In O&M and reliability, false-alarm burden, lead time, and maintenance utility should sit alongside F1 score or AUROC. Without such benchmark discipline, the field will continue to overinterpret local numerical gains that do not transfer cleanly across domains or tasks.

8.1.2. Open or semi-open data infrastructures

A second near-term priority is the development of open or semi-open data infrastructures that improve comparability without ignoring commercial and operational sensitivities. This need is acute because the domains differ sharply in data access: offshore wind has the richest operational records but much of the evidence remains proprietary; wave and tidal rely heavily on site-specific archives, pilot deployments, and experimental platforms; OTEC remains particularly thin in long-duration operational data. In practice, fully open raw datasets will not always be realistic. A more actionable route is the development of semi-open infrastructures: standardized metadata, curated subsets, agreed taxonomies for logs and failure labels, benchmark-ready partitions, and shared reporting templates that permit external comparison even when full industrial datasets cannot be released. Such infrastructures would do more to improve cumulative knowledge than another round of isolated model comparisons on incomparable data.

8.1.3. Physics-informed learning and hybrid modeling

A third near-term direction is the focused development of physics-informed learning and hybrid models for the parts of the field where data scarcity and extrapolation are already well understood bottlenecks. This direction matters especially in wave energy, tidal design and control, and OTEC, where operational datasets remain limited and purely black-box learning is often poorly matched to the engineering requirement. The practical research need is not to attach physics constraints to models in a symbolic way, but to identify where physical structure genuinely improves extrapolation, stability, inverse identification, or constrained control. Near-term work should therefore prioritize settings where governing structure is known, field data are limited, and the engineering consequence of extrapolation failure is material. Equally important, these models should be evaluated with calibrated uncertainty and under off-nominal scenarios rather than only under in-distribution tests.

8.1.4. Graph learning for wake-coupled farms and interaction-rich arrays

A fourth near-term priority is graph learning, especially for offshore-wind forecasting and surrogate modeling where the evidence base is already strongest. This direction matters because wake-coupled farms and, in principle, wave or tidal arrays are interaction networks rather than independent-device collections. In the near term, graph learning is most actionable where the relational structure of the engineering system is already operationally important and where enough data exist to support comparative evaluation. Offshore wind currently meets that condition most clearly. By contrast, direct evidence in wave and tidal arrays remains thinner, so near-term work should focus on physically grounded graph construction, comparison against non-graph baselines, and careful evaluation of transfer across layouts and flow conditions rather than on premature claims of generalized array intelligence.

8.1.5. LLM/VLM-driven O&M and inspection workflows

A fifth near-term priority is the development of LLM/VLM-driven O&M and inspection workflows under explicit human oversight. This direction matters because some of the highest-value offshore tasks now sit in free-text maintenance logs, work orders, inspection notes, blade imagery, and other semi-structured or unstructured records that classical signal-processing pipelines cannot fully exploit. In the near term, the most realistic agenda is not autonomous diagnosis, but grounded workflow support: maintenance-log labeling, knowledge retrieval, inspection triage, defect description assistance, and multimodal support tools that remain auditable and reviewable by human experts. This is especially relevant in offshore wind, where the data ecosystem is richest, but the same workflow logic could later benefit wave, tidal, and OTEC once suitable records and evaluation protocols exist. The near-term research priority is therefore groundedness, retrieval quality, provenance tracking, and auditability—not claims of autonomous maintenance reasoning.

8.2. Long-term emerging directions

8.2.1. Neural operators for many-query offshore prediction and design

Among the longer-term directions, neural operators are particularly important because many offshore problems involve repeated evaluation of parameterized physical responses rather than single-instance prediction. This is relevant to wake modeling, flow-response approximation, and repeated surrogate evaluation inside design or control loops. The reason neural operators matter in marine renewable energy is that high-fidelity hydrodynamic, aero-hydro-servo-elastic, or thermodynamic simulation remains too expensive for many-query tasks at operational timescales. However, neural operators remain a longer-term direction because their present evidence is strongest in a relatively narrow set of offshore-wind wake applications. Broader deployment will require better understanding of stability, boundary-condition sensitivity, transfer across operating regimes, and comparison with alternative reduced-order or hybrid surrogates.

8.2.2. Generative models for rare faults, missingness, and distribution support

Generative models also belong in the longer-term research agenda. Their importance in marine renewable energy follows from a persistent statistical problem: offshore O&M data are often imbalanced, fault labels are sparse, and missingness is endemic. Under those conditions, generative methods may help with anomaly-sensitive monitoring, structured imputation, representation learning, and selected augmentation tasks. Yet this direction remains exploratory in an important sense. The strongest current evidence is concentrated in offshore-wind condition monitoring and in selective tidal image-augmentation settings; much less is established across wave, tidal, and OTEC more broadly. The central research challenge is not simply to produce synthetic examples, but to determine when generated distributions preserve operationally meaningful failure structure, when they improve maintenance decisions rather than only offline classification metrics, and how they should be calibrated and audited in certification-sensitive settings.

8.2.3. Graph learning beyond offshore wind

A related longer-term direction is the extension of graph learning beyond offshore wind into wave farms, tidal arrays, and eventually multi-service offshore infrastructures. The methodological rationale is strong: these are interaction-rich systems in which devices influence one another through shared flow, structural coupling, or coordinated operation. However, unlike offshore wind, these settings do not yet benefit from equally rich and reusable evidence. The longer-term research task is therefore to determine when graph structure remains identifiable and useful under sparse deployment data, changing array geometry, and limited long-duration validation. This is likely to require closer integration with physical simulators, array-aware benchmarking, and stronger pilot-scale data release than the field currently provides.

8.2.4. LLM/VLM systems as grounded multimodal maintenance copilots

The longer-term horizon for LLM/VLM-driven O&M is not generic automation, but the development of grounded multimodal maintenance copilots that can combine text, imagery, operating context, and retrieved historical records in a way that remains auditable and operationally responsible. This matters because offshore maintenance decisions increasingly depend on fragmented evidence distributed across logs, inspection histories, work orders, images, and sensor context. The longer-term challenge is to connect these streams without sacrificing provenance, reviewability, or safety. That is a more demanding problem than near-term workflow support. It will require standardized maintenance ontologies, retrieval-grounded generation, abstention logic, calibrated confidence, and robust human-oversight protocols. For the present, this remains exploratory, especially outside offshore wind.

8.2.5. Integrated benchmarked ecosystems rather than isolated model studies

Finally, the longer-term trajectory of the field should be toward integrated benchmarked ecosystems in which models, datasets, validation protocols, and domain-specific reporting standards evolve together. This is where the earlier clusters converge. Physics-informed learning, neural operators, graph learning, generative models, and LLM/VLM systems will not become decision-relevant in marine renewable energy through isolated performance improvements alone. They will matter only when they are anchored to repeatable datasets, transparent baselines, comparable evidence levels, and clearer routes from pilot evidence to deployment-oriented validation. In this sense, benchmark creation and semi-open infrastructures are not merely supporting tasks; they are the enabling conditions that make the more advanced methodological directions scientifically cumulative rather than episodic.

Taken together, the future agenda is therefore asymmetric and strategically ordered. In the near term, the field should prioritize benchmark creation, semi-open data infrastructures, physics-informed and hybrid models in sparse-data settings, graph learning where interaction structure is already evidenced, and grounded human-in-the-loop LLM/VLM workflows. Over the longer term, the more exploratory agenda includes neural operators for many-query offshore prediction, generative models for rare-fault and incomplete-data regimes, graph learning for wider array and multi-service infrastructures, and multimodal maintenance copilots with auditable reasoning chains. This progression is more consistent with the current evidence base than a generic claim that “AI will transform the sector.” The relevant question is not whether transformation will occur, but which research directions are technically aligned with the data, physics, and validation realities of marine renewable energy today.

9. Conclusion

This review has argued that artificial intelligence in marine renewable energy should be interpreted through an evidence-weighted engineering lens rather than through algorithmic breadth alone. Across wave, tidal, offshore wind, and OTEC, the relevant question is not whether AI has been applied, but whether a given claim is supported by a suitable data regime, meaningful baselines, task-appropriate metrics, and validation maturity consistent with the intended engineering use. The E1–E5 evidence ladder provides the comparative logic: E1–E2 evidence is useful for concept testing and constrained proof of principle, E3 provides partial operational relevance, and E4–E5 provide the strongest basis for deployment-oriented inference. The literature therefore does not support a single uniform conclusion about “AI in marine renewable energy”; it supports a tiered conclusion about where AI is already field-relevant, where it is promising but validation-limited, and where it remains emerging.

Offshore wind currently provides the strongest deployment-oriented evidence, especially in operational forecasting and O&M/reliability. This strength reflects the availability of SCADA records, met-ocean and NWP-linked data, condition-monitoring and vibration streams, inspection imagery, alarms, and maintenance records. In these settings, AI is already a credible engineering tool for short-horizon prediction, normal-behavior modeling, anomaly detection, lead-time estimation, inspection triage, and maintenance decision support. Even here, the conclusion is bounded: cross-farm transfer, proprietary data, label inconsistency, concept drift, and governance remain material constraints. Nevertheless, offshore wind currently provides the clearest evidence that AI can deliver field-relevant value in marine renewable energy systems.

Wave and tidal energy show genuine and technically meaningful progress, particularly in short-horizon forecasting, constrained control, and surrogate-assisted design/optimization. However, their evidence remains more frequently bounded by E1–E3 validation, including simulation, laboratory or tank testing, site-specific field records, short campaigns, and pilot-scale settings. In wave energy, AI is most defensible as a site-level forecasting enhancer and as support for constrained control and design-space exploration. In tidal systems, AI is most defensible where it improves on harmonic or physical baselines under local disturbance, or where surrogate-assisted design and targeted monitoring address costly hydrodynamic or maintenance problems. These advances are important, but they should not yet be interpreted as broadly transferable operational maturity.

OTEC remains the least mature AI domain in the review. The most defensible current uses are compact process prediction, state estimation, supervisory support, and experimentally bounded optimization under strongly structured thermodynamic constraints. Most evidence remains component-level, rig-scale, experimental-platform, or simulation-supported. OTEC is therefore a technically plausible but still emerging AI application area, and claims of mature predictive maintenance, autonomous operation, or deployment-grade digital twins would exceed the current evidence base.

The post-2020 methodological shift changes the field's opportunity structure, but not the need for evidence discipline. Classical ML remains useful for bounded, tabular, moderately sized, or well-benchmarked prediction and diagnosis tasks. Physics-informed models and PINNs are valuable where sparse data and physical constraints must be combined. Neural operators are promising for many-query surrogate evaluation and wake or flow-field approximation. Graph learning is appropriate where farms, arrays, or sensor systems are relational. Generative and diffusion models can help with rare faults, missing data, imbalance, and inspection workflows, but require validation against real operational distributions. LLM/VLM systems are best framed as human-in-the-loop support for logs, inspection imagery, work orders, and maintenance reasoning, not as autonomous offshore decision-makers. In all cases, methodological novelty should not be treated as equivalent to engineering maturity.

The asymmetry in this review's domain coverage is therefore substantive rather than structural. Offshore wind receives more detailed treatment because it has richer operational datasets and stronger E4–E5 validation; wave and tidal sections are more cautious because their AI evidence is more often E1–E3 and site-specific; OTEC is shorter and more bounded because its evidence base remains sparse and experimental. This does not imply that wave, tidal, or OTEC are less important marine renewable technologies. It indicates that their AI evidence base is currently less mature.

Future progress will depend less on adding further algorithm variety and more on strengthening the evidence infrastructure around marine-energy AI. The most important priorities are field-duration datasets, transparent and task-appropriate benchmarks, semi-open data infrastructures, transfer-aware validation, uncertainty calibration, and certification-grade evaluation. These are the conditions required for AI in marine renewable energy to move from promising technical demonstration toward dependable offshore engineering practice.

CRediT authorship contribution statement

Amin Mirzaei: Formal analysis, Writing – original draft. **Mohamadreza Pazhouhan:** Formal analysis, Writing – original draft. **Koroush Rezanejad:** Supervision, Writing – review & editing. **Mohammad Jahanbakht:** Formal analysis, Writing – original draft. **C. Guedes Soares:** Funding acquisition, Supervision, Writing – review & editing.

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Appendix A

Table A1
Cross-domain dataset visibility and benchmarking constraints in AI-enabled marine renewable energy studies

Domain	Task family	Data regime and representative sources	Dataset visibility/ scale	Labels or targets	Typical evidence level	Main benchmarking constraint	References
Wave energy	Operational wave-farm forecasting	Mutriku Wave Power Plant operational SCADA production data combined with ERA5 wave-energy flux, oceanic, and atmospheric predictors	Single-site operational OWC wave plant; 2014–2016; 2855 screened hourly cases; 1427 training cases and 1428 testing cases; predictions at 4 h steps up to 24 h; plant data available for research but not a fully open benchmark	Average electric power generated across active turbines over the previous 5 min; forecast horizons from 4 h to 24 h	E4	Operationally relevant evidence, but results are highly site- and technology-dependent; Mutriku OWC plant data should not be benchmarked directly against buoy-only SWH forecasting or simulation-only WEC control studies	Serras et al. (2019)
Wave energy	Wave-condition and wave-resource forecasting	Buoy records, NREL wave-resource data, national marine data platforms, reanalysis products, WAVEWATCH III/ COAM products, and public or semi-public environmental archives	Mostly measured or archive-based records; examples include NREL wave-resource data from 2010, sampled at 3 h intervals, Queensland coastal records for Emu Park and Townsville, and Beibu Gulf/South China Sea gridded SWH and wind-speed data for 2018–2019 at 1 h and 1/40° × 1/40° resolution	Significant wave height, wave period, wave-energy flux, wind speed, or wave-energy output derived from forecasted wave height	E3–E4	Forecasting skill depends strongly on site, horizon, temporal resolution, spatial resolution, preprocessing/ decomposition strategy, and whether the target is measured SWH or model-derived wave energy	(Raj and Prakash, 2024; Sareen et al., 2023; Song et al., 2022; Zhao et al., 2023)
Wave energy	WEC control and model identification	Numerical hydrodynamic models, WEC-Sim-type simulations, wave-tank experiments, model-scale WEC tests, DeepONet/ operator-learning data, LSTM/RNN control and excitation-force prediction data	Mostly simulation or laboratory evidence; representative high-quality experimental case: 1:50 hinged-raft WEC, 20 wave-tank runs, two sea states, two peak-enhancement factors, five random phases, 128 Hz wave and motion capture, each run about 9.5 min model scale/1.1 h full scale	Excitation force, WEC heave/pitch motion, absorbed power, PTO force, hinge position, RAO, or control reward	Mostly E1–E2; occasional E3 when validated against independent tank experiments	Tank/model-identification success is not deployment evidence; comparison requires matched device type, sea-state diversity, scale ratio, sampling rate, target variable, and control constraints	Zhao et al. (2023)
Wave energy	WEC design, layout, and surrogate-assisted optimization	CFD, BEM/Nemoh, potential-flow solvers, response surface methodology,	Mostly simulation-generated; examples include CETO layout datasets with 16 WEC positions and	Absorbed power, capture width, hydrodynamic coefficients, mooring loads,	Mostly E1; occasional E2 when simulation is benchmarked	Surrogate speed-up is meaningful only when accuracy loss, solver dependence, feasibility	(Azad and Herber, 2023; Azad et al., 2025; Barone et al., 2025;

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Table A1 (*continued*)

Domain	Task family	Data regime and representative sources	Dataset visibility/ scale	Labels or targets	Typical evidence level	Main benchmarking constraint	References
		Gaussian process regression, LSTM/ GPR hybrid surrogates, active-learning CFD sampling, CETO layout datasets, and RSM/GA/ANN optimization outputs	absorbed-power variables, 72,000 rows per site dataset, RSM/CCD/i-optimal simulation campaigns, and CFD-based active-learning samples for extreme mooring-load prediction	CWR, LCOE-related indicators, drag, geometry parameters, or extreme load statistics	against tank data or higher-fidelity CFD	constraints, and validation against independent or higher-fidelity data are reported; solver agreement is not field validation	Katsidoniotaki et al., 2025)
Wave energy	Monitoring, fault diagnosis, and predictive maintenance	Mutriku operational wave-plant data, OWC/ PTO operating signals, gearbox vibration signals, simulated and experimental gearbox datasets, Bayesian network/ fault-tree reliability structures, and WEC subsystem fault simulations	Dataset visibility is uneven; Mutriku provides real measured experimental/ operational evidence; gearbox studies combine rigid-flexible simulation with laboratory vibration experiments; BN/FTA studies are mainly simulation or model-based and do not provide a large public operational dataset	Health states, fault classes, vibration features, probabilistic fault states, voltage/ current/power deviations, anomaly indicators, or early fault probabilities	E2–E4	Rare faults, restricted access to plant data, simplified gearbox experiments, incomplete field class distributions, and component-to-field transfer limit reproducibility and deployment claims	(Boutkhil Mohamed et al., 2025; Kang et al., 2024; M'Zoughi et al., 2024; Mortazavizadeh et al., 2023)
Tidal energy	Tidal-current forecasting and numerical-model correction	ROMS simulation, ADCP observations, tide gauges, Cook Inlet/Eastport current records, Pentland Firth simulated data, harmonic analysis residuals, SSA/HRA forecasting, MLP/ LSTM/attention-ResNet models	Site-specific field and simulation datasets; examples include Zhoushan ADCP observations from 30 May–9 July 2021 with 5700 samples, Cook Inlet data from 18 May–29 June 2005 at 6 min sampling, Eastport data from 1 July–30 August 2000 at 6 min sampling, and Pentland Firth simulation data	U/V current components, corrected velocity fields, tidal-current speed, harmonic residuals, or derived tidal power	E3; mixed E1/ E3 where simulated and measured data are combined	Forecasting comparisons require matched horizon, sampling rate, site nonlinearity, harmonic baseline, online-training assumptions, and clear separation between simulated and real ADCP data	(Monahan et al., 2023; Zhang and Zhao, 2023)
Tidal energy	Subsurface current estimation and resource assessment	HF radar surface-current measurements combined with ADCP subsurface current profiles, Celtic Sea/ WaveHub-type field measurements, and ANN-based vertical current estimation	March–December 2012 field campaign; ANN trained using two weeks of ADCP data and tested for longer forecast windows up to six months; strong local evidence but limited spatial transferability	Subsurface current velocity profiles and downstream power estimates	E3	Strong local evidence, but model transfer failed even over short spatial separations because of water-column differences; not a general resource model without retraining	Bradbury and Conley (2021)
Tidal energy	Wake, array, FSI, and hydrodynamic surrogate modeling	LES, URANS, RANS, CFD, actuator-disk simulations, flume experiments, scaled turbine benchmarks, FSI models, CNN autoencoder wake reconstruction, and turbine-array surrogate models	Mostly simulation/ lab data; representative cases include lab-scale wake-validation experiments, model-scale FSI rotor simulations, CNN models trained on LES turbine-array flow fields, a single-row three-turbine training case, two-row validation cases, and large CPU-cost reductions relative to LES/URANS	Velocity fields, turbulence statistics, pressure, thrust, power coefficient, blade deformation, equivalent stress, wake profiles, and turbine-array wake fields	E1–E2; occasional E3 where validated against independent laboratory or LES data	Solver-generated labels, scale effects, simplified rotor/ blade assumptions, and wake-model fidelity dominate; CFD/LES surrogate accuracy should not be treated as operational tidal-array evidence	(Badshah et al., 2018; Zhang et al., 2023b, 2024c)
Tidal energy	Monitoring, ecological	Water-tunnel/ video datasets,	Mostly laboratory-scale image evidence;	Three-class biofouling labels:	Mostly E2	Augmentation and laboratory	Rashid et al. (2024b)

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Table A1 (*continued*)

Domain	Task family	Data regime and representative sources	Dataset visibility/ scale	Labels or targets	Typical evidence level	Main benchmarking constraint	References
	sensing, and image-based diagnosis	laboratory tidal-turbine platforms, image-based biofouling emulation, CNN transfer learning, soft-voting ensemble models, and limited environmental monitoring datasets	SMU dataset: 25 original images extracted from videos and augmented to 1980; LU dataset: 1200 original samples augmented to 5490; LU turbine is 1:20 scale with 0.279 m rotor diameter and 0.83 m/s inflow	clean, lightly fouled, densely fouled; visual blade-condition classes		emulation may overstate readiness; results are not directly comparable with real subsea inspection, long-term ecological monitoring, or operational integrity-management workflows	
Tidal energy	Emerging wake-pattern learning	CFD-generated oscillating-foil vorticity fields, CNN-LSTM wake classification, convolutional autoencoder clustering, and k-means++ wake-pattern grouping	Simulation-only; 46 oscillating-foil kinematic cases; four wake-pattern clusters identified; average fold accuracy about 91% for the classification algorithm	Wake-pattern classes, vortex-structure clusters, and kinematics–wake correlations	E1	Useful for post-2020 wake-pattern learning, but not mature tidal-turbine deployment evidence; oscillating-foil wake classes should not be equated with full-scale tidal turbine array performance	Moreira et al. (2022)
Ocean thermal/ OTEC	Thermal-resource and upper-ocean heat estimation	World Ocean Database profiles, in situ temperature profiles, Argo CTD, satellite SST/SSHA, AVHRR, ORAS5, WOA18, climatological D26, ocean heat-content products, and ANN/deep-learning reconstruction models	Strong archive visibility; representative cases include more than 25,000 in situ profiles for ANN training and more than 8000 independent validation profiles in the Indian Ocean; large Argo/WOD/ WOA-based datasets in later OHC studies	TCHP, OHC, TSL, subsurface temperature, upper-ocean heat content, or depth-layer temperature fields	E3–E4	Strong for resource characterization and ocean thermal mapping, but not direct evidence of OTEC plant performance, plant control, heat-exchanger operation, or deployment maturity	(Ali et al., 2012; Kondeti and Palanisamy, 2025; Su et al., 2022)
Ocean thermal/ OTEC	Subsurface temperature reconstruction and ocean thermal structure	Multisource satellite observations, Argo gridded data, EN4, IAP, Ishii, ARMOR3D, DORS product, ConvLSTM, and global deep ocean remote-sensing reconstruction	Large-scale spatiotemporal products; representative case: DORS global ocean subsurface-temperature product from 1993 to 2020, upper 2000 m, monthly gridded reconstruction with multiple depth layers	Multidepth subsurface-temperature reconstruction and 3D thermal structure	E3–E4	Useful for ocean thermal mapping and climate-scale thermal structure, but not comparable to OTEC cycle-control, heat-exchanger, pumping, or plant-level AI models	Su et al. (2022)
Ocean thermal/ OTEC	OTEC-adjacent climate and upper-ocean prediction	Upper-ocean temperature anomaly fields, wind-stress anomalies, SST fields, CMIP6 simulations, SODA/ ORAS5/GODAS reanalysis, IRI/ NMME-style ENSO/ climate forecasts, and transformer-based 3D-Geo-former models	Large climate-model and reanalysis datasets; representative case: 3D-Geoformer trained on 23 CMIP6 simulations from 1850 to 2014, validated using SODA and ORAS5 reanalysis, and assessed against GODAS for ENSO-related prediction	Wind-stress anomalies, SST anomalies, upper-ocean temperature anomalies, and 3D ENSO-related thermal fields	E3–E4	Climate-prediction evidence should not be treated as direct OTEC resource-control, OTEC plant optimization, or deployment evidence; relevance is contextual and resource-oriented	Gao et al. (2023)
Ocean thermal/ OTEC	Component-supporting design and hydrodynamic optimization	CFD/Fluent simulations, Latin hypercube samples, neural-network surrogates, GA/ Pareto optimization, teardrop buoy geometry, and ocean-thermal-energy-driven	Simulation-centered; representative case uses neural-network and genetic-algorithm optimization of teardrop buoy geometry, with CFD-based validation and hydrodynamic comparison of	Drag, drag coefficient, drainage volume, buoy geometry parameters, and hydrodynamic performance indicators	E1 with limited experimental anchoring	Useful for component-level surrogate optimization, but not evidence of operational OTEC-system performance, heat-engine efficiency, or plant-level control maturity	Zhao et al. (2024a)

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Table A1 (*continued*)

Domain	Task family	Data regime and representative sources	Dataset visibility/ scale	Labels or targets	Typical evidence level	Main benchmarking constraint	References
		profiling buoy design	optimized versus baseline designs				
Ocean thermal/ OTEC	OTEC feasibility, techno-economic, and contextual evidence	Secondary literature, historical OTEC designs, cost models, country-level feasibility/ resource reviews, NPV/LCOE-style calculations, and resource-site screening	No AI training dataset; evidence is mainly techno-economic and contextual; examples include historical OTEC assessments, island/country feasibility studies, coastal site screening, and cost-per-kWh estimates	Capital cost, feasibility, temperature-gradient threshold, resource potential, LCOE/cost per kWh, technical-readiness, and component-scaling indicators	Contextual evidence only	Useful for explaining why OTEC AI evidence remains weak and why operational plant datasets are scarce; should not be mixed with ML validation evidence	(Su et al., 2022; Zhao et al., 2024a)
Offshore wind	Offshore wind forecasting and resource assessment	Floating lidar buoys, ERA5 pressure-level data, MCP-corrected ERA5 profiles, RU-WRF/NWP, turbine-level power records, SCADA-style power data, offshore meteorological variables, and LSTM/EEMD/ ConvLSTM models	Generally stronger visibility than wave/ tidal/OTEC; examples include Amrumbank West hourly wind-power data from 2015 to 2023 for a Siemens SWT-3.6-120 offshore turbine, and public 2-year floating-lidar data at four Dutch North Sea locations with 10 min wind profiles from 30 to 200 m	Wind speed, hub-height wind, vertical wind profile, wind-power output, and error-corrected short-term forecasts	E3–E4; E5 only for broad multi-site, multi-year operational records	Forecasting claims must be interpreted by horizon, target type, site, spatial scale, turbine-specific versus regional data, and access condition; turbine-power forecasting should not be benchmarked directly against lidar-based wind-profile extrapolation	(Melalkia et al., 2025; Rouholahnejad and Gottschall, 2025)
Offshore wind	Graph learning, missing-data reconstruction, and multi-node forecasting	Multi-node offshore wind-speed records, wind-farm graph structures, Westermost Rough turbine power time series, spectral graph theory, k-nearest-neighbor reconstruction, and graph-learning models	Operational or semi-operational multi-node evidence; representative case: Westermost Rough offshore wind farm with 35 turbines and two years of 10 min power data; China Sea graph-learning records report multi-node structure but sample visibility is less complete	Future wind speed, missing power-generation values, graph-imputed turbine power, or multi-node forecasting outputs	E3–E5 depending on data provenance and task; imputation is not control or diagnosis	Graph/imputation results should not be compared directly with physical wake models, turbine-health diagnosis, or structural-load estimation; missing-data reconstruction is a data-quality task	(Liu et al., 2023; Pierrot and Pinson, 2025)
Offshore wind	Wake, digital twin, and predictive control	LES/SOWFA wake fields, SWiFT-style validation data, SpinnerLidar validation, physics-informed digital twins, CNN-LSTM/ MPC control simulations, and wake-steering/ partial-operation cases	Mostly simulation-generated; typical cases include two- and nine-turbine LES/control studies, greedy/wake-steering/partial-operation scenarios, and field-anchored lidar validation; exact sample counts are not consistently reported across studies	3D wake velocity fields, rotor-effective wind speed, farm power, wake-control commands, and digital-twin state estimates	E1 with occasional E3 anchoring	Important post-2020 methodological evidence, but not operational deployment evidence unless field validated under real farm-control conditions	Zhang and Zhao (2023)
Offshore wind	SCADA-based condition monitoring, fault diagnosis, fatigue, and RUL	Operational SCADA, alarm logs, O&M logs, event logs, accelerometers, SHM sensors, strain gauges, component-temperature data, and normal-behavior/RUL models	Strong operational examples: Donghai Bridge 12-month dataset from 34 offshore WTs with more than 50 SCADA readings at 30 s sampling; jacket-foundation SHM/ SCADA/acceleration data transformed into 430 10-min features; EDP offshore turbine gearbox-pump dataset with 28,633 records and 82	Fault classes, temperature residuals, probabilistic RUL, DEL targets, anomaly indicators, attention weights, and component-health states	E4; potentially E5 if multi-turbine/multi-year validation is broad enough	Strongest deployment-oriented AI evidence, but reproducibility is limited by proprietary SCADA/ logs, sparse fault labels, site specificity, and restricted public access	(Santos et al., 2022; Su et al., 2024; Zhang et al., 2025b)

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Table A1 (*continued*)

Domain	Task family	Data regime and representative sources	Dataset visibility/ scale	Labels or targets	Typical evidence level	Main benchmarking constraint	References
			variables over about half a year				
Offshore wind	Public/ simulated fault benchmarks	Simulated generator inter-turn short-circuit fault signals, public Zenodo benchmark, current-signal datasets, and ML severity/phase-classification models	Public simulated benchmark; 75 ITSCF fault scenarios plus one healthy case; 76 scenarios in total; generator current simulated at 4 kHz; public Zenodo/ GitHub dataset	Fault severity and faulty-phase labels	E1	Excellent for algorithm comparison and reproducible benchmarking, but not evidence of operational offshore fault maturity because signals are simulated rather than field-measured	Yan et al. (2025)
Offshore wind	Remote sensing, asset detection, inspection support, and human-in-the-loop O&M	Sentinel-1 SAR time series, Google Earth Engine, CFAR sea-clutter mitigation, random forest classification, mathematical morphology, 4C Offshore validation, drone/ inspection-support data, and XAI/VR-style support systems	Remote-sensing evidence is relatively transparent; representative case detects offshore wind turbines from 2015 to 2021 in the Yellow Sea of China and North Sea of Europe, identifying 2120 and 3649 turbines by 2021 and reporting 93.67% agreement with 4C Offshore ground truth	Turbine/non-turbine detection labels, asset-presence indicators, spatial change labels, inspection-support targets, and anomaly-explanation targets	E3–E4 depending on task	Asset detection, inspection logistics, and XAI support should not be benchmarked against SCADA fault diagnosis, RUL prediction, or wind-power forecasting because the targets and evidence forms are different	Xu et al. (2022)
Offshore wind	O&M scheduling and structural inspection decision support	Simulated maintenance environments, PHM state information, resource-decision models, reinforcement-learning maintenance policies, fracture-mechanics/NDT inspection frameworks, and crack-growth models	Mostly model-based or simulation-based evidence; representative examples include a simulated 50-turbine wind farm with multiple maintenance crews and structural inspection/crack-growth models tied to IEC/DNV design load cases	RL rewards, maintenance actions, failure-class probabilities, crack-size variables, inspection-risk variables, and cost/ risk outcomes	E1/contextual model-based evidence	Useful for decision architecture and inspection logic, but not dataset-rich operational AI evidence unless coupled with real O&M histories, inspection records, and field-validated degradation trajectories	(Amirafshari et al., 2021; Pinciroli et al., 2021)

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