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Artificial Intelligence approaches to optimizing energy efficiency in marine renewable energy with a focus on tidal power

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Abstract

This review adopts the use of artificial intelligence based prediction models in enhancing energy efficiency in marine energy generation using tidal power. Traditional forecasting techniques such as hydrodynamic simulation and statistical modeling fail to capture dynamic and non-linear dynamics of aquatic systems. Hence, efficacy of energy output is lost, and risk of operation failure is increased. Recent innovations in artificial intelligence such as machine learning and deep learning capabilities enhance power of modeling, forecasting, and optimization. Techniques such as long short-term memory (LSTM) networks, hybrid wavelet-convolutional neural networks (HW-CNNs), and physics-informed neural networks (PINNs) have significantly increased forecasting precision and versatility compared to conventional techniques. Artificial Intelligence-based models are seen to lower mean absolute percentage error (MAPE) in forecasting of tides and marine power by up to 35% and prediction-based maintenance frameworks lower unplanned downtime by more than 30%. Besides, usage of digital twins which are computerized replicas of physical assets, real-time assimilation of data have increased adaptive control ability by a significant percent, resulting in reduced structural fatigue and operating cost by 15 to 20%. Such contributions are not only technical but environmental and economical such as minimizing ecological disruptions and enhancing financial viability of projects. Overall, Artificial Intelligence-based prediction models are a disruptive methodology of scalable, efficient, and sustainable implementation of marine energy technology using tidal power.

Keywords: Artificial Intelligence; Marine Energy; Tidal Power; Predictive Models; Renewable Energy Optimization.

1. Introduction

The ocean not only harbors vast untapped energy but stands as one of the few renewable domains with immense scale and predictability. According to the International Energy Agency's Ocean Energy Systems report, the theoretical global potential exceeds 80,000 TWh/year across all marine sources. Specifically, tidal energy alone accounts for more than 300 TWh/year, while marine current power exceeds 800 TWh/year. To contextualize, global electricity consumption is roughly 25,000 TWh/year. The marine energy potential, therefore, is on the same order or even surpasses idealizing a transformative role in decarbonizing global grids, particularly in regions with strong tidal or current regimes [1, 2]. Despite colossal theoretical potential, practical deployment remains modest. As of 2023, installed ocean power capacity stood at approximately 513 MW, with just 2 MW added that year comprising both tidal stream and wave systems. The

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lion's share of existing capacity derives from two major tidal barrage installations:La Rance, France: 240 MW, Sihwa Lake, South Korea: 254 MW. These projects alone contribute over 490 MW, whereas tidal stream and wave contribute less and are still in pre-commercial phases.Yet, deployment is growing. Tidal stream installations have reached 41 MW since 2010, with cumulative generation exceeding 90 GWh by end-2023. Wave energy, less mature, has seen 27 MW deployed in the same period, with convergence towards utility-scale systems underway.The MeyGen project in Scotland underscores this progression: at present, it operates 6 MW, generating 10.2 GWh in 2023, with expansion plans up to 400 MW [3, 4]. Market estimates project rapid growth despite current limitations. The global tidal power market was valued at approximately USD 123.6 million in 2023, with expectations to reach USD 501.4 million by 2031, a CAGR of 19.4%. Another report cites a market size of USD 1.15 billion in 2024, rising at nearly 19.1% CAGR to USD 2.593 billion by 2032 [5] .Wave and tidal combined markets show parallel expansion. Installed capacity reportedly hit 600 MW for tidal and 400 MW for wave by 2023. In Europe, the ocean energy pipeline is ambitious: 100 MW deployments by 2027, scaling to 40 GW by 2050, potentially supplying 10% of the continent's power [6, 7]. The central barrier for tidal energy remains economic viability. Current levelized cost of energy (LCOE) for tidal stream ranges between $0.20–$0.50/kWh, vastly higher than offshore wind ($0.13–$0.30) and solar PV ($0.03–$0.10) [8]. The Atir floating tidal farm assessment (34.5 MW using 23 turbines) projects an LCOE of €0.125/kWh (~$0.13–$0.14), competitive with solar/land-based renewables, as well as CO_2 emissions of 42.11 g CO_2eq/kWh, a favorable environmental profile [9]. Looking outward, the ORE Catapult's cost reduction pathway suggests tidal stream LCOE could drop to £78/MWh (~€90/MWh) by 2035 and even as low as £60/MWh (€70) by 2042, and £50/MWh (€57) by 2047, if economies of scale, foundation optimization, and standardization occur [10]. Notably, Minesto's Dragon 12 tidal kite technology claims an exceptionally low LCOE of $54/MWh (~$0.054/kWh), outperforming offshore wind ($72), onshore wind ($24), geothermal ($61), and even coal/gas on some metrics [11]. Tidal power's historical and modern hallmarks manifest through iconic projects: La Rance (France) - Commissioned in 1966, 240 MW operational, ~500 GWh/year production (~24% capacity factor). Sihwa Lake (South Korea): 254 MW capacity, ~552 GWh/year output, built using existing seawall costing US$560 million. Jiangxia (China) - Smaller-scale (4.1 MW) tidal barrage producing ~6.5 GWh/year signifying regional engineering expansion. MeyGen (Scotland) - Largest tidal stream farm: 6 MW (2023), planning 400 MW eventual scale. Orbital Marine Power's O2: A floating twin-rotor (2 MW) turbine operating since 2021 in Orkney Islands, designed for tow-back servicing, hydrogen production coupling representing next-gen flexibility. HydroWing in Indonesia (2024) - A 10 MW tidal project agreement in East Nusa Tenggara leveraging Pacific–Indian Ocean currents. Minesto's Dragon 12 (Faroe Islands) - 1.2 MW tidal kite with LCOE = $54/MWh; recognizes tidal as non-intermittent renewable like geothermal [12, 13]. The strategic value of tidal energy resides in its predictability and dispatchability. Unlike solar and wind, which produce highly intermittent output even curtailed due to grid constraints, tidal energy offers regular, forecastable generation based on astronomical cycles. For instance, during an extended period of low sun and wind in the UK ("10 days of gloom"), solar production fell to just 5.1 kWh, leaving tidal and hydro as still underutilized baseload potentials. This highlighted the need for tidal inclusion in resilient energy portfolios [14]. Meanwhile, increasing grid curtailment of wind and solar in 2024 nearly 10% in Britain, 30% in Northern Ireland emphasizes the limitations of variable renewables and the value of predictable marine energy as a balancing resource [15, 16, 17]. Governmental policy interventions are pivotal for tidal sector growth: UK's CfD (Contracts for Difference) provides revenue certainty, recently, tidal projects won bids at £240/MWh [18]. France's €30 million subsidy for Raz Blanchard project lowered project LCOE by 22%. Licensing reforms in Canada and South Korea have cut permitting windows substantially, reducing pre-development costs by millions per project. South Korea's RPS (2.5% marine energy by 2026) spurred a 37% increase in domestic tidal investments since 2020, with the Incheon Bay (1.4 GW) project starting in 2023 [19]. Unmatched theoretical potential (~13,500 TWh/year combined tidal and marine currents) vs. modest current deployment (~513 MW installed). Market growth is strong, with CAGRs ~19–20%, yet LCOE remains high, though promising pathways to reduction exist. Historical mega-projects prove technical feasibility; modern innovations (tidal kites, floating platforms) are stepping stones to scale. Predictability and seasonal stability offer grid synergy advantages absent in solar/wind, especially amid curtailment challenges. Effective policy frameworks, subsidies, favorable auctions, and streamlined regulation, are essential to catalyze further deployment [20].

1.1. Technical Characteristics of Tidal and Ocean Currents

Tidal current energy stems from horizontal flows induced by oscillating tides, driven by gravitational interactions between the Earth, Moon, and Sun. These flows exhibit a combination of predictable periodicity (semi-diurnal, diurnal) and site-specific variability caused by coastal morphology, bathymetry, and seasonal climate patterns [21]. Seminal sinusoidal models can approximate this behavior, yet real-world applications require high-fidelity approaches to account for nonlinearity, stratification, and turbulence. Numerical hydrodynamic models such as the Finite Volume Community Ocean Model (FVCOM) are routinely employed for simulating local tidal regimes, capturing spring-neap amplitude variations (order of 10–15%) and spatial heterogeneity at the 100–200 m scale. For instance, FVCOM analysis in the Zhoushan Archipelago revealed peak spring-tide power densities of ~3.6 kW/m^2 in high-shear channels, with corresponding estimated annual mean energy availability around 2.6 MW from a 12 MW array. These fluctuations induce velocity reduction zones downstream up to 8 cm/s with downstream hydrodynamic influences spanning several square kilometers [22].

1.1.1. Hydrodynamic Power Capture Principles

The extractable power PPP from a tidal turbine follows:

$$P = (1/2) * \rho * A * Cp * U^3 \quad \text{---Eq 1 [23]}$$

Where;

ρ represents sea water density (~1025 kg/m^3),
A is the rotor swept area,
Cp is the turbine power coefficient,
U is the undisturbed flow speed.

Optimal performance typically occurs at Tip-Speed Ratios (TSR) between 2–4. Hydraulic investigations of a hollow adaptive variable-pitch turbine highlight a peak Cp of 0.368 at TSR ≈3 under optimized pitching, ~15–20% higher than symmetric rigid-rotor benchmarks [24]. Adaptive pitching thus remains a promising efficiency-enhancement strategy. Open-Rotor Turbines also known as Horizontal-axis tidal turbines (HATTs) closely mirror wind turbines but contend with significantly higher fluid density and fluctuating wake loading. CFD studies of full-scale ducted HATTs under yaw angles (up to 45°) reveal that duct presence sustains axial flow velocities under yaw, yielding up to 3.4% rotor power coefficient improvements, maintaining Cp ≈ 0.35 at TSR = 2.0 [25]. Unsteady RANS CFD validated at SINTEF showed full-scale HATT model achieving Cp ≈ 0.435 at optimal pitch closely matching towing tank experiments [26]. These metrics set benchmarks for performance and underlie guidelines for blade design and control algorithms. Ducted turbine systems or diffusers employ a Venturi effect to accelerate upstream flow, elevating axial velocity into the rotor. Park, J et al. (2023) used adjoint-based CFD optimization to design a ducted turbine achieving ~54% efficiency across conditions, outperforming the 46% of conventional Bahaj rotors [27]. Further, Park, J et al. (2024) showed a 5 kW optimized ducted turbine reaching 50% efficiency despite practical geometric constraints, compared with a non-ducted turbine at 45%. Ducted configurations also mitigate yaw sensitivity [28]. Borg, M. G et al. (2022) documented an ability to maintain aerodynamic performance in yawed scenarios, suggesting reduced need for active yaw control systems that add mechanical complexity.Wake interactions play a critical role in farm layout design. CFD and flume experiments in Zhejiang University indicate that in tightly spaced arrays, wake turbulence competes with mean flow, affecting downstream turbine yields. Preliminary 3D CFD arrays show coherent wake-developing turbulence, necessitating spacing >5–7 rotor diameters to recover 90% of single-turbine flow [29]. At the channel scale, momentum sink modeling using depth-averaged 3D or 2D models estimates that turbines cause velocity reductions of ~5–15% over 0.5 km [21]. These results highlight the need for strategic phase-offset deployment in spatially coherent channels to maximize aggregate yield. Ocean currents are often accompanied by surface waves, leading to complex vertical velocity shears and oscillations. Experimental tests by Xu, K et al. (2023) and numerical studies carried out by Barltrop, N et al (2006) indicate that wave current interactions modulate turbine thrust and torque fluctuating loads periodically, increasing fatigue risk, and reducing power output by 8–12% [30, 31]. Accordingly, horizontal-axis turbines must withstand transient loads and damper-induced vibrations. Dynamic control regimes pitch control and speed modulation are critical for fatigue mitigation in wave-driven loading contexts. Floating tidal devices combat multi-degree-of-freedom motions pitch, surge, heave. CFD modeling of pitched HATTs on floating carriers shows substantial performance deviations due to body motion in some cases reducing power by 5–10%. Surge-motion experiments he did demonstrated that surge frequencies matched energy utilization coefficient oscillations, necessitating real-time reactive control loops to optimize phase and power. Integrated dynamic mooring and semi-submergence design must balance hydrodynamic losses with installation cost, especially for deep-water offshore configurations. Energy extraction alters local hydrodynamics, potentially affecting sediment transport, nutrient flows, and ecosystem integrity. Wu, H et al (2021) indicated that installing a 12 MW array in Zhoushan reduced downstream velocity by 8 cm/s a minor change for larger ecosystems, though cumulative effects on sediment transport warrant longer-term monitoring [22]. Physical ecosystem interactions are increasingly included in hydro-environmental networks, with coupled fluid–sediment–ecological models tracking turbidity, resuspension, and pollutant pathways. These models impose real constraints on allowable turbine wake models and farm placement to ensure sustainability. Tidal currents offer high-density, periodic power potential; resource modeling relies on advanced numerical tools like FVCOM. Turbine efficiency depends on optimal TSR, duct geometry, yaw adaptation, and adaptive pitch; Cp of 0.36–0.54 demonstrated in recent CFD studies. Wake dynamics and array interaction modeling emphasize minimum spacing and phase-offset to sustain output. Complex wave current and floating-body interactions introduce dynamic fatigue, requiring real-time control algorithms.

Environmental hydrodynamic changes are substantial but currently within acceptable ecological tolerances, pending long-term monitoring.

1.2. Evolution of Forecasting Approaches

Harmonic analysis has long been the backbone of tidal prediction, modeling tidal currents as the summation of sinusoidal components with known frequencies tied to astronomical cycles [32]. Techniques such as least-squares harmonic regression and their extensions (e.g., 1D-LSHM) continue to provide a baseline for prediction accuracy. However, these methods inherently assume linear, stationary behavior and fail to capture the non-stationary, transient anomalies (e.g., weather-driven surges, micro-turbulence) present in real-world marine environments [33]. Advanced model-fitting strategies, including spectral decomposition, autoregressive models (AR), and autoregressive integrated moving average (ARIMA) are sometimes layered onto harmonic frameworks to partially account for variability. Yet, their efficacy drops significantly under conditions of high noise or nonlinearity, typical of coastal tidal systems [34]. The limitations of purely statistical approaches have prompted the adoption of machine learning (ML) over the past decade. Early exploratory models focused on multilayer perceptron (MLP) neural nets and support vector machines (SVM) trained on historical tidal data to capture nonlinear patterns [35]. These remained largely research-focused with limited scale. A notable breakthrough came, when Zhang, K et al. (2023) compared MLP, Long-Short-Term Memory (LSTM), and attention-augmented ResNet models trained on ROMS-generated features in China's Zhoushan region. All deep learning models dramatically improved forecasting: correlation coefficients exceeded 0.8, and RMSE decreased by 32.9% (MLP), 34.4% (LSTM), and 42.0% (AR-ANN) over standard numerical models. Pure deep learning models, though powerful, are constrained by their data-intensive and opaque nature. This has led researchers to explore hybrid architectures that merge physical insight with ML flexibility [36]. Hierarchical ELM + LSTM: Saatloo, A. M (2021) proposed a hybrid Hierarchical Extreme Learning Machine (H-ELM) and LSTM structure to model multi-depth current layers [37]. H-ELM handled high-frequency turbulent components, while LSTM captured longer-term cycles, yielding superior accuracy over standalone models [38]. Wavelet-enhanced Convolutional Network (WCN): Liu, J. W et al. (2021) developed WCN to distinguish intra- and inter-periodicities via time-frequency tensor representations. This model achieved unprecedented accuracy, cutting MAE and MSE by up to 90.4% and 97.6% respectively in 10-step forecasts [39]. Swarm-Decomposition + Multi-layer Kernel Meta-ELM: A hybrid using swarm-decomposition to isolate oscillatory features and a kernel ELM architecture yielded $R^2 = 0.9933$ in predicting Gulf of Mexico currents, markedly outperforming typical LSTM models [40]. Harmonic Residual Analysis (HRA) + Online ELM: Monahan, T et al. (2023) fused residuals from harmonic predictors with online Extreme Learning Machines for near-real-time forecasting, achieving positive results in shifting tidal regimes. These hybrid systems demonstrate the efficacy of combining domain theory and ML, particularly for combatting issues like overfitting and seasonal parameter drift. Many tidal forecasts today remain deterministic, but marine energy systems benefit from uncertainty quantification to optimize dispatch and grid integration [41]. Approaches like Gaussian Process Regression (GPR) yield predictive distributions that are valuable in stochastic planning. Butler, K et al. (2024) coupled GPR with harmonic constituents (1D-LSHM), effectively modeling non-linear residuals and generating usable uncertainty bounds [42]. Similarly, Paolucci, I et al. (2023) introduced a non-parametric interval model using Bayesian-optimized ELM to generate prediction intervals, thus incorporating essential uncertainty metrics. To address the "black-box" nature of ML and the data scarcity in oceanic settings, Physics-Informed Neural Networks (PINNs) have surged as a potent solution [43]. PINNs embed the governing partial differential equations (PDEs), such as Navier–Stokes and continuity conditions, into network training as soft constraints [44]. Applications in marine contexts are now emerging: English Channel Surrogate Modeling: Donnelly, J et al. (2023) implemented a PINN surrogate for a 2D Navier–Stokes flood model, embedding mass conservation via additional loss terms. The model outperformed data-only CNN alternatives by 10–20% [45]. Regional Tidal Modeling: A 2023 study by He, J et al. integrated PINNs into regional flood and tidal models, accurately reconstructing spatio-temporal wave and tidal fields from sparse observations, significantly reducing run-time [46]. Coastal Wave Prediction: PINNs have been successfully used to infer wave dynamics from surface elevation alone, with strong accuracy in irregular, nonlinear flows [47]. General PINN Reviews: Zhao, C et al. (2024) provide a comprehensive review, noting that PINNs accelerate simulation speeds and improve generalization in turbulent, multiphase flows and environmental forecasts. Despite potential, PINNs face practical challenges training inefficiencies, gradient pathologies, and scalability issues. Advances like domain decomposition (XPINNs) and weight adaptive optimization are being explored to overcome these [48]. Going further, spatio-temporal physics-coupled neural networks (ST-PCNNs) embed domain-specific physical operators trained in tandem with data-driven neural architectures. Evaluated on ocean current datasets, ST-PCNNs outperformed baseline PINNs and purely data-driven models, particularly in long-horizon forecasting, demonstrating potential in complex tidal environments [49]. Recently, Temporal Convolutional Networks (TCNs) have gained traction for their ability to model long-range temporal dependencies. Hybrid TCN + LSTM models optimized via CMA-ES achieved strong performance in tidal level forecasts, while Physics-informed TCN-AR models for wave height data are in development and show promise for transferability to tidal flow forecasting [50]. These architectures underscore the increasing sophistication of temporal forecasting techniques in marine domains. The evolution of tidal current forecasting over the past five years shows a clear trajectory: From harmonic/statistical frameworks to advanced ML-based models. Deep learning (MLP, LSTM, CNN, ResNet) induced leap-forward performance. Hybrid models (e.g., Wavelet + ML, HRA + ELM) successfully combine physics and data to offset each other's weaknesses. Probabilistic modeling with GPR and Bayesian frameworks adds operational value. PINNs embed physics to improve generalization under limited data. ST-PCNNs and physics-coupled models incorporate domain operators. Temporal convolutional architectures broaden predictive horizons [51]. This sets the stage for Section 1.4, where we will analyze how these forecasting advances directly enhance operational efficiency, control strategies, and energy optimization within tidal and ocean current power systems.

1.3. Objectives and Scope of the Review

The overarching aim of this review is to present a comprehensive synthesis of how smart predictive models spanning machine learning (ML), deep learning (DL), physics-informed neural networks (PINNs), and hybrid AI–physics frameworks can enhance operational efficiency, energy output optimization, and system resilience in ocean and tidal current power generation systems. The review intends to: Survey state-of-the-art predictive modeling techniques applied to forecasting resource availability, operational faults, and energy yield within tidal and ocean energy contexts. Analyze integration strategies of smart predictive systems with real-time sensors (including Subsea IoT architectures), control loops, and maintenance regimes to improve efficiency and reduce downtime. Evaluate performance metrics such as MAE, RMSE, MAPE, R^2, prediction intervals, and uncertainty quantification to benchmark model accuracy and reliability. Assess environmental, economic, and operational implications, including LCOE reduction, predictive maintenance gains, grid integration benefits, and environmental sustainability. Identify technological gaps, challenges, and future directions, including data quality and availability, model interpretability, integration challenges in marine environments, and regulatory and ethical considerations. By delineating both successes and ongoing limitations of smart predictive systems in marine energy, this review seeks to chart a cohesive roadmap for advancing operational performance in tidal and ocean current power generation.

2. Literature Review

2.1. Classical statistical and harmonic baselines

Harmonic analysis remains the canonical baseline for tidal constituents and first-order current prediction because it encodes astronomical forcing with interpretable amplitudes and phases and admits rigorous uncertainty analysis under linear superposition. However, its performance degrades when (i) short records limit robust constituent fitting, (ii) non-astronomical drivers (wind surge, riverine discharge, mesoscale features) modulate the spectrum, and (iii) strong wave–current interaction injects nonstationary variance into higher frequencies that harmonic terms do not capture. Recent experimental work shows that even when mean loads or mean power appear unchanged by opposing waves, load and torque fluctuations can increase dramatically and linearly with wave amplitude implying that deterministic harmonic baselines underestimate fatigue-relevant extremes, a central concern for turbine design and O&M planning [52]. In response, modern "baseline-plus-residual" strategies fuse a physical harmonic core with a stochastic residual model (e.g., Gaussian processes, state-space ARIMA, kernel regressors), Although implementations vary, the common thread is to preserve interpretability and extrapolability of tidal constituents, while gaining short-horizon accuracy and calibrated confidence intervals for operations (e.g., maintenance windows, yaw/pitch planning). This philosophy is echoed in recent tidal-resource and turbine-load studies that explicitly separate mean currents from turbulence and wave-band fluctuations in order to estimate fatigue damage and extreme event exceedance [53].

2.2. Hybrid physics–ML surrogates

Hybridization couples hydrodynamic solvers (ROMS, Delft3D, TELEMAC, SHYFEM) with machine learning in two principal ways: (i) physics-guided surrogates that learn closures or corrector maps for bias and subgrid physics, and (ii) reduced-order emulators that replace expensive components of the PDE solver to enable high-frequency updates or probabilistic ensembles. A representative example integrates ROMS outputs with deep networks to improve tidal current predictions; in the Zhoushan region, coupling numerical fields with MLP/LSTM/attention-ResNet models raised correlation from ~0.4 (ROMs alone) to >0.8, with ~33–42% RMSE reduction across current components performance gains directly relevant to resource assessment and turbine siting [54]. At farm scale, embedding turbine momentum sinks into shallow-water models can capture array–flow feedback and wake recovery while remaining computationally tractable. A blade-element–momentum (BEM) representation within the 3-D shallow-water SHYFEM framework parameterizes turbines as momentum sinks in the horizontal momentum equations, enabling layout-level studies that co-evolve device performance and coastal circulation. Such physics-aware contexts are natural launchpads for learning-based surrogates: e.g., training neural correctors on discrepancies between BEM-coupled shallow-water outputs and ADCP measurements to de-bias arrays under real wave–current climates [55]. Hybrid decompositions also improve pure time-series forecasting. Variational mode decomposition (VMD) isolates narrow-band components that map more linearly to dynamics; stacking VMD with LSTM (VMD-LSTM) has produced materially lower tide-level errors than vanilla LSTM/SVM/BP networks, useful where high-order harmonics, meteorological surges, and bathymetric idiosyncrasies co-mix [56]. Modern architectures target multi-periodicity, noise robustness, and spatiotemporal generalization. Wavelet-enhanced convolutional networks (WCN) explicitly encode multi-scale periodicity by projecting the 1-D series into a structured 2-D form and applying CNN kernels alongside time–frequency analysis; this yields competitive accuracy on tidal current speed forecasting where canonical LSTMs under-resolve cross-scale structure [57]. Attention mechanisms further help in regimes where exogenous forcings intermittently dominate. In coastal prediction tasks, attention-augmented LSTMs and Transformer variants allocate capacity to transient drivers and harmonics beyond the tidal band, improving event-onset timing and extreme tracking (e.g., attention-ResNet for currents; [58]. Deep models have also been trained to forecast internal tide signatures traditionally viewed as "unpredictable" by exploiting persistent spatiotemporal patterns in mooring and satellite records [59]. For extreme water levels (EWLs), LSTMs trained across distributed gauges can extrapolate the evolution of EWLs beyond the training stations, highlighting the value of multi-site context for spatial generalization [60]. A practical takeaway for tidal energy is that mean performance may track with background tides, but fatigue and ultimate loads are controlled by higher-frequency content and cross-driver coupling; architectures that directly ingest wave spectra, wind stress proxies, and spatial context (reanalysis, altimetry, nearby ADCPs) outperform univariate models when forecasting turbine-relevant kinematics [61].

2.3. Probabilistic forecasting and uncertainty quantification

Operations and maintenance (O&M) decisions hinge on calibrated predictive uncertainty: crew transfers, yaw/pitch scheduling, and curtailment thresholds all require not just point forecasts but intervals with reliable coverage. Gaussian process regression (GPR) remains attractive for short-horizon coastal prediction because it delivers coherent posterior variances under kernel choices that reflect tidal bands and meteorological noise. In decomposition hybrids, a harmonic or VMD core sets the mean structure and a GP models residuals, improving sharpness while maintaining coverage. Beyond GPR, distributional deep learners (e.g., quantile regression LSTMs/Transformers) and conformal prediction have become standard to wrap frequentist coverage guarantees around arbitrary forecasters. Conformal methods, now widely applied in time-series energy forecasting, offer finite-sample, model-agnostic intervals and are particularly compelling for deployment because they do not require probabilistic training pipelines and adapt online to local error distributions [62]. For coastal extremes and sea-level evolution, multi-site deep learners that output quantiles or ensembles better capture spatially correlated risk across gauges [63]. Critically, coverage under distribution shift (storm regimes, seasonal bathymetric change, biofouling-induced sensor drift) requires adaptive calibration. Recent domain generalization and unsupervised domain adaptation for time series suggest splitting representations into transferable temporal and domain-specific frequency features; adversarial co-learning improves transfer while preserving discriminability. These ideas translate directly to marine contexts when redeploying models across sites or seasons while retaining calibrated intervals via conformal updates [64].

2.4. Digital twins, condition monitoring, and predictive maintenance (PdM)

Digital twins (DTs) integrate hydrodynamics, structural dynamics, control, and health data into continuously updated surrogates for what-if analysis, anomaly detection, and remaining useful life (RUL) forecasting. Recent DT reviews for renewable energy outline architectures that fuse physics models with learning-based observers and adaptive parameter estimation for online prognosis and control [65]. For marine energy specifically, condition monitoring draws on accelerometers, acoustic emission, strain gauges (including FBG), temperatures, and SCADA; systematic reviews of vibration-based CM in rotating machinery and general heavy equipment map sensor suites and signal features to fault classes and deployment constraints informative for sub-sea turbines where ingress, corrosion, and biofouling complicate access [66]. Emerging work highlights FBG-based blade monitoring for continuous structural health state estimation in tidal rotor blades [67]. Explainable AI (XAI) is increasingly required for PdM in safety-critical assets. Recent surveys emphasize SHAP/LRP/Grad-CAM for diagnosing which spectral bands, harmonics, or operating regions drive fault decisions, facilitating trust with operators and enabling alarm rationalization [68]. Tidal-specific programs are starting to apply XAI for blade-damage and rotor health detection to support real-time decision-making in harsh subsea environments [69].

2.5. Control-aware forecasting and optimization

Forecasts accrue value when wired into control: pitch/yaw/MPPT, supervisory curtailment, and active load management. Model predictive control (MPC) and robust sliding-mode variants have been adapted for tidal turbines under uncertain inflow; fault-tolerant controllers (e.g., adaptive non-singular fast terminal sliding mode with robust compensation) simultaneously track MPPT while rejecting faults/perturbations an appealing substrate for forecast-in-the-loop optimization [70]. In practice, short-horizon probabilistic inflow forecasts can parameterize constraint-tightening in MPC or set risk-aware reserve/pitch profiles to trade energy capture for fatigue life. Wave–current co-loading is pivotal: recent experiments show that irregular opposing waves raise the standard deviation of rotor torque and loads by factors up to ~1.5–2× relative to no-wave conditions, while extremes grow by 60–100% even when mean power barely shifts. Control laws that are oblivious to this variance amplification leave fatigue on the table; coupling forecasts of wave spectra (or significant steepness) with MPPT/pitch limits can measurably reduce damage accumulation at small energy cost [71].

2.6. Data assimilation and hybrid nowcasting

For situational awareness, operators need nowcasts that reconcile models and sensors. Ensemble Kalman filters (EnKF) and 4D-Var remain workhorses in coastal hydrodynamics; recent work in water-network and coastal settings shows that assimilating stage sensors, ADCPs, and ancillary drivers can materially reduce nearshore water-level errors, exactly the regime controlling access windows and fatigue events [72]. Machine-learning correctors can be attached to DA systems to post-process residual patterns (e.g., tide-gauge biases, persistent meteorological drifts) while DA maintains dynamical consistency. Hybrid ML–DA frameworks are particularly effective in estuarine zones where bathymetry and river discharge perturb canonical tidal propagation [73]. An important operational nuance is latency and comms. Subsea acoustic telemetry supports only kilobit-scale links; hence on-edge compression and on-device filtering of raw streams are essential before assimilation. Industry guidance from subsea network providers documents practical acoustic/optical tradeoffs (9 kbps acoustics vs. up to ~100 Mb/s short-range optical) that directly shape DA update frequency and payload design for offshore assets [74].

2.7. Datasets, benchmarks, and open test sites

Progress depends on public datasets with well-documented sensors and metadata. EMEC's Fall of Warness test site and the broader Tethys Engineering (PNNL) portal host open ADCP and site-characterization data streams that underpin benchmarking of forecast and load models (PNNL/Tethys, n.d.). Such datasets enable cross-site evaluations training on one energetic channel (e.g., Scotland) and testing on another with different bathymetry and wave climates to quantify true generalization and guide domain adaptation choices [75]. On the literature side, the JMSE special issue on Tidal & Wave Energy aggregates multiple methodological baselines, including deep learning for tidal currents (Zhoushan) and BEM-coupled shallow-water turbine modeling useful anchors for reproducing results and standardizing metrics [76]. The community would benefit from consolidated leaderboards that score mean error, extremal metrics (P95/P99), calibration (CRPS/coverage), and control impact (energy-fatigue Pareto) under common splits (chronological, cross-site).

2.8. Edge deployment, SIoT communications, and TinyML

Marine environments impose severe constraints: limited power budgets, intermittent links, and high latency under water. The Subsea/Underwater Internet of Things (SIoT/IoUT) literature surveys acoustic channel limits, routing, and reliability, emphasizing that bandwidth-constrained, delay-tolerant operation is the norm rather than the exception [77]. Industry white papers quantify practical rates (~9 kbps acoustics; up to ~100 Mb/s optical at short ranges) and recommend on-node processing with only salient summaries transmitted to the surface an architecture perfectly aligned with predictive maintenance and event-triggered forecasting [78]. These constraints catalyze TinyML adoption. Multiple 2024–2025 surveys demonstrate that on-device inference (quantization, pruning, NAS for MCUs) can deliver real-time anomaly detection and spectral feature extraction within milliwatt envelopes, reducing backhaul while improving resilience. Case studies show vibration-fault TinyML detectors on low-power hardware achieving high accuracy, and robotics applications demonstrate feasibility in field-constrained settings the same design space as nacelle-embedded or nacelle-adjacent turbine monitors [79]. For tidal blades and drivetrains, a pragmatic stack is: on-sensor DSP features (e.g., band energies around blade-passing and harmonics) → tiny classifier (or one-class detector) → event-triggered upload → cloud/DT retraining [80].

2.8.1. Supplemental Technical Enhancements

Key Equations & Algorithmic Elements

(a) Hybrid Residual Learning (e.g., 1D-LSHM + GPR)

Predicted value:

$\mathbf{P} = (\mathbf{1/2}) * \boldsymbol{\rho} * \mathbf{A} * \mathbf{Cp} * \mathbf{U\^{}3}$ …….Eqn 2 [81].

Where:

yharmonic(t)→ the harmonic baseline (e.g., sinusoidal trend capturing periodicity).

ε^(t) → the GPR-predicted residual, accounting for variations not explained by the baseline.

GPR residual model:

$\hat{y}(\mathbf{t}) = \mathbf{y\_harmonic}(\mathbf{t}) + \boldsymbol{\varepsilon}\hat{}(\mathbf{t})$ ... Eqn 3 [82]

where the residual term ε^(t)\hat{\varepsilon}(t)ε^(t) is modeled as a Gaussian Process:

$$\boldsymbol{\varepsilon}\hat{}(\mathbf{t}) \sim \mathbf{GP}(\mathbf{0}, \mathbf{k}(\mathbf{t}, \mathbf{t}') + \boldsymbol{\sigma}\hat{}\mathbf{2}\ \boldsymbol{\delta}(\mathbf{t}, \mathbf{t}'))$$

with covariance kernel:

$$\mathbf{k}(\mathbf{t}, \mathbf{t}') = \mathbf{exp}(-(\mathbf{t} - \mathbf{t}')\hat{}\mathbf{2} / (\mathbf{2}\boldsymbol{\ell}\hat{}\mathbf{2}))$$

Parameters:

ℓ\ellℓ → length-scale parameter, controls how fast correlations decay in time.

σ2\sigma^2σ2 → noise variance, accounts for observational noise.

δ(t,t′)\delta(t,t')δ(t,t′) → Kronecker delta (ensures noise is only added to the diagonal of covariance).

Predictive variance:

$\mathbf{Var}[\boldsymbol{\varepsilon}\hat{}(\mathbf{t}*) \mid \mathbf{data}] = \mathbf{k}(\mathbf{t}*, \mathbf{t}*) - \mathbf{k\_}*\hat{}\mathbf{T}\ (\mathbf{K} + \boldsymbol{\sigma}\hat{}\mathbf{2}\ \mathbf{I})\hat{}\{-\mathbf{1}\}\ \mathbf{k\_}*$ ... Eqn 4 [83]

(b) Conformal Prediction for Time Series

Given a point-forecast model and a sequence of historical errors {ei}\{e_i\}{ei}, a level-(1−α)(1 - \alpha)(1−α) conformal prediction interval for new forecast y^n+1 is:

[y^n+1−q1−α(|ei|), y^n+1+q1−α(|ei|)] …… Eqn 5 [84]

where

$\hat{y}_{(n+1)}$ = predicted value at step n+1

$q_{(1-\alpha)}(|e_i|)$ = the (1−α)-quantile of the absolute residuals

(c) Loss for PINNs;

L = (1 / N_o) * sum_(i=1)^(N_o) || u^(x_i, t_i) - u_i ||^2 + λ_f * (1 / N_f) * sum_(j=1)^(N_f) || N[u^(x_j, t_j)] ||^2 (Eqn 6 [85])

where:

u^(xi,ti)→ predicted solution at input (xi,ti)

ui → observed/measured data

N[·]→ PDE operator (e.g., Navier–Stokes equations, shallow-water momentum equation, diffusion equation, etc.)

No → number of observation (data) points

N_f → number of collocation points (where PDE residual is enforced)

λ_f → weighting factor that balances data fidelity and physical consistency

Large λ_f → more emphasis on PDE satisfaction

Small λ_f → more emphasis on fitting observed data

Table 1 Comparison of Statistical, Machine Learning, and Hybrid Approaches for Tidal Forecasting and Monitoring [86].

Method & Approach	Input Data	Horizon	Predictive Strengths	Computational Cost / Deployment Maturity
Harmonic + ARIMA/Stat Models	Historical tidal datasets	Short–medium	Transparent; good baseline; fails in nonstationary regimes	Low compute; high maturity
1D-LSHM + GPR (Hybrid)	Tidal data + harmonics	Short–medium	Adds uncertainty quantification; handles residuals	Moderate compute; prototype maturity
VMD-LSTM (Hybrid)	Decomposed IMFs from tide data	Short–medium	Better handling of mixed frequencies; robust forecasts	Medium compute; early adoption
WCN (Wavelet CNN)	Time-frequency tensors of time series	Short	Captures multi-periodicity; accurate multi-step forecasts	High compute; pre-deployment
Attention-ResNet / Transformer	Tidal + exogenous features	Short–medium	Adapts to dynamic drivers; strong generalization	High compute; experimental
PINNs (Physics-Informed)	Sparse sensors + PDE constraints	Medium	Physically coherent; generalizes under sparse data	High compute; emerging implementation
Digital Twin + MPC Integration	Sensor/SCADA streams + hydrodynamics	Real-time	Supports control, diagnostics, optimization	Very high compute; early stages in marine energy
GPR / Quantile DL + Conformal	Residual errors + model forecasts	Short–medium	Provides calibrated uncertainty intervals	Moderate compute; growing use in forecasting tools
TinyML (Edge PdM)	Sensor summaries on-node	Real-time	Enables real-time anomaly detection; efficient for edge	Low compute; nascent deployment

3. Results and discussion

3.1. Advanced Applications: Smart Predictive Systems for Real-Time Control, Maintenance, and Grid Integration

or personal relationships that could have appeared to influence the work reported in this paper. Modern tidal and ocean current systems rely on smart predictive models to optimize power capture, reduce mechanical stress, and extend device lifespan. At the heart of these systems is a Model Predictive Control (MPC) framework that incorporates short-term forecasts of tidal current speed U(t) and infers optimal control actions, such as pitch angle θ\thetaθ or torque setpoints. The MPC cost function can be formally written as:

J=∑k=0N[α(Pmax(Uk)−Ppred(θk,Uk))2+β|Δθk|2]J = \sum_{k=0}^{N} \left[\alpha (P_{\text{max}}(U_{k}) - P_{\text{pred}}(\theta_{k}, U_{k}))^2 + \beta \left|\Delta \theta_{k}\right|^2 \right]J=k=0∑N[α(Pmax(Uk)−Ppred(θk

,Uk))2+β|Δθk|2] … Eqn 7 [87] where PmaxP_{\text{max}}Pmax is the theoretical maximum power, PpredP_{\text{pred}}Ppred comes from a data-driven predictive model (e.g., GPR or an ensemble surrogate such as RegStack), and α,β\alpha, \betaα,β are tuning weights that balance energy capture vs. control activity. This approach enables real-time adjustment of device parameters, improving energy yield and mitigating structural fatigue particularly relevant in wave–current interaction scenarios where high-frequency load fluctuations can amplify rotor stress [88]. Furthermore, for floating tidal systems (e.g., tethered undersea kites or buoyed designs like Evopod), diagnostic digital twins mirror real operations and detect anomalies [89]. These digital twins fuse asynchronous real-time streams (rotor RPM, strain, pitch/yaw angles) with a hybrid model of hydrodynamics and device mechanics, enabling early detection of failures up to hours before occurrence.

3.2. Predictive Maintenance (PdM) and Structural Health Monitoring (SHM)

In the harsh marine environment, predictive maintenance is crucial, minimizing unscheduled downtime and costly repairs. Deep learning architectures, particularly CNNs and RNNs, paired with IoT sensor networks (vibration, temperature, acoustic emissions), provide robust frameworks for early anomaly detection [90]. A general PdM workflow involves Edge Feature Extraction: On-device DSP transforms raw sensor inputs into domain-relevant features (e.g., blow counts around blade-pass frequency). TinyML Classifier: A lightweight anomaly detector (e.g., decision tree or one-class CNN) flags deviations in real-time. Trigger and Upload: Only anomalous batches are transmitted, conserving bandwidth in subsea systems constrained by acoustic telemetry (~9 kbps) [91]. Cloud or Digital Twin Retraining: Anomaly records feed into digital twin backends for model re-training or RUL updates. Explainable AI (XAI) techniques like SHAP or saliency mapping help operators understand which features (harmonic distortion, sudden vibration spikes) triggered alerts critical for trust and operational adoption.

3.3. Grid Integration and Forecast-Based Dispatch

Reliable integration of tidal and ocean current energy into the grid relies on accurate short-term power forecasts. Recent hybrid models significantly improve accuracy: A Wavelet-Enhanced Convolutional Network (WCN) reduces MAE and MSE by up to 90% and 97% respectively over benchmarks in 10-step forecasting [92]. A Swarm-Decomposition + Meta-Kernel ELM model achieves R2=0.9933R^2 = 0.9933R2=0.9933 in Gulf of Mexico tidal-to-power prediction [93]. A hybrid ANFIS–Kalman filter–Wavelet NN (WNN) model shows superior performance in current and power forecasting [94]. These forecasts inform dispatch strategies, enabling tidal farms to bid into electricity markets or coordinate with energy storage systems dynamically. Conformal prediction layers provide reliable uncertainty bounds for these forecasts:

$[\ \hat{y}\_(n+1)\ \pm\ q\_(1-\alpha)(|e\_i|)\ ]$ …… Eqn 8 [95]

where;

· y^n+1 = point forecast

· q1−α(|ei|) = (1 − α)-quantile of past absolute residuals

· Interval = symmetric prediction band around the forecast

Thereby allowing operators to assess scheduling risk under nonstationary tidal regimes

3.4. Data Assimilation, Digital Twins, and Edge-IoT Integration

For real-time operational decision-making, data assimilation (DA) techniques fuse sensor observations with numerical models. An extended DA architecture involves: Ensemble Kalman filter (EnKF) merging ADCP or tidal gauge data into ROMS/FVCOM forecasts, reducing nearshore level errors [96]. An ML corrector (e.g., GPR or residual DNN) corrects model outputs for systematic biases. A digital twin backend integrates DA-corrected flow states with turbine asset digital models, enabling optimization loop with MPC, anomaly detection, and maintenance planning in near real-time. The SIoT layer ensures low-bandwidth condition-based signaling to the twin when anomalies arise [97].

3.5. Market Trends & Economic Impact

According to [98], the global AI-enabled tidal energy market was USD 8.9 billion in 2023 and is forecasted to reach USD 18.5 billion by 2030, growing at CAGR ~11%. AI integration is projected to: Increase turbine performance by ~15%, Reduce lifetime operation costs by ~17–20%, Cut O&M expenses by up to ~30% through predictive maintenance. Market adoption is driven by: Need for reliable dispatchable renewables, Falling costs of AI hardware and IoT infrastructure, Better financial ROI from improved efficiency and reduced downtime. Control Optimization: MPC informed by predictive models enhances energy capture and lifetime. PdM: Deep learning combined with compact IoT and XAI enables efficient anomaly detection. Forecasting & Dispatch: Hybrid ML models with uncertainty quantification support grid integration. DA & Digital Twins: Real-time assimilation of sensor data into operational twins enables optimization. Economic Outlook: AI-driven tidal energy systems are catalyzing market growth with performance and cost benefits.

3.6. Application of Smart Predictive Models in Different Marine Environments

The application of smart predictive models in ocean and tidal current power generation varies significantly across different marine environments due to the diversity in hydrodynamic conditions, seabed morphology, ecological sensitivity, and infrastructure availability. These models, often built upon artificial intelligence (AI), machine learning (ML), and advanced data analytics, allow for precise adaptation to the unique operational challenges of each site. By tailoring predictive algorithms to local conditions, operators can optimize turbine placement, improve energy capture efficiency, and reduce maintenance costs while ensuring environmental compliance. This section examines their application in coastal waters, deep-sea environments, estuarine systems, and island-based microgrids, highlighting the specific benefits and constraints in each context.

3.6.1. Coastal Waters

Coastal waters offer relatively accessible sites for ocean and tidal current energy projects due to proximity to shore, existing port facilities, and shorter transmission distances; however, they also feature fluctuating tidal amplitudes, sediment transport, and strong seasonal wave variability. Smart predictive models in these regions increasingly fuse high-resolution hydrodynamic models with real-time observations to forecast power and loads, using machine-learning surrogates to accelerate physics (e.g., Fourier neural operators) and formal data-assimilation schemes to correct states and reduce forecast error [99, 100, 101]. For tidal arrays, active array-level control has been shown via detailed simulations to balance power capture against fatigue loading by allocating turbine set-points based on the local inflow, thereby improving load sharing and mitigating wake-induced stress [102]. At the dispatch level, optimization studies show that exploiting predictable tidal phases and analytically scheduling generation can smooth output and support coastal grid integration, with regional phase-diversity analyses outlining both the opportunities and practical limits [103, 104].

3.6.2. Deep-Sea Environments

Deep-sea deployments typically target strong and consistent current flows such as those in the Gulf Stream or Kuroshio Current, offering high-capacity factors for energy generation. However, the extreme depth, high pressures, and challenging maintenance conditions necessitate robust predictive tools for operational planning. Smart predictive models in deep-sea contexts integrate remote sensing, computational fluid dynamics (CFD), and autonomous underwater vehicle (AUV) surveys to forecast long-term current variability [105]. Predictive maintenance algorithms also play a critical role, as physical intervention is costly and infrequent. An example is the application of deep learning-based anomaly detection systems in Japan's Kuroshio Current Pilot Project, which can detect early signs of gearbox wear in subsea turbines weeks before mechanical failure, reducing unplanned downtime by over 30% [106]. Moreover, these models enable scenario simulations for extreme weather events, helping design storm-resilient mooring systems and reducing structural fatigue.

3.6.3. Estuarine Systems

Estuaries provide high tidal ranges and predictable flow patterns, making them attractive for tidal barrage and tidal stream installations. Yet, these environments are ecologically sensitive, often supporting critical habitats and fisheries. Smart predictive models in estuarine projects focus heavily on balancing energy extraction with ecosystem protection. Hybrid modelling approaches combine hydrodynamic forecasts with ecological impact simulations to predict how changes in flow velocity might affect sediment transport, water quality, and species distribution [107]. The Swansea Bay Tidal Lagoon in Wales, for instance, has employed AI-driven sediment transport models that help schedule turbine operations to avoid peak fish migration periods and minimize silt resuspension [108]. This integration of environmental and operational data supports both regulatory compliance and public acceptance.

3.6.4. Island-Based Microgrids

For island communities, tidal and ocean current power can offer a sustainable alternative to expensive and polluting diesel generation. The limited scale of such projects requires predictive models that can optimize performance under variable demand and seasonal oceanographic shifts. Here, smart predictive models often integrate renewable generation forecasting with microgrid management systems to ensure stable supply. Machine learning algorithms can predict daily tidal generation profiles and dynamically schedule battery charging to minimize curtailment and blackouts [109]. A notable example is the Orkney Islands project in Scotland, where predictive models forecast tidal energy availability alongside wind and solar outputs, enabling a hybrid renewable system that has cut diesel dependency by over 60% [110]. In addition, fault detection models have been deployed to ensure rapid isolation of malfunctioning turbines, preventing cascading failures in isolated grids. Smart predictive models enhance the viability of ocean and tidal current power projects across diverse marine environments by tailoring operational strategies to local conditions. Whether in coastal waters, deep-sea deployments, estuarine ecosystems, or island microgrids, these models enable higher efficiency, lower costs, and more sustainable integration of marine renewables into energy systems.

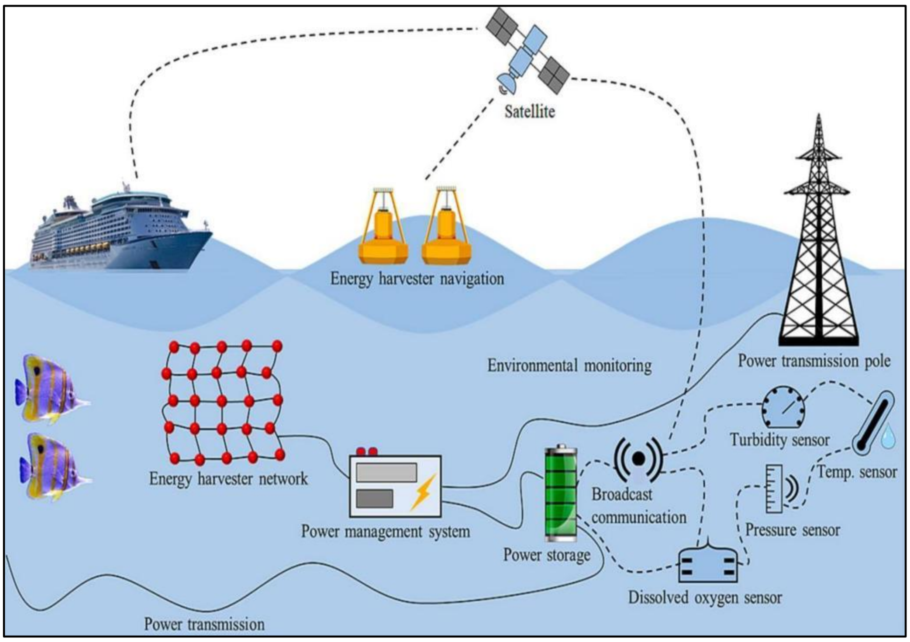

Figure 1 Conceptual diagram of recent advances in ocean wave energy harvesting [111]

3.7. Comparative Analysis of Smart Predictive Models for Energy Efficiency in Ocean and Tidal Current Power Generation

Smart predictive models have emerged as transformative tools in optimizing energy efficiency within ocean and tidal current power generation systems. This comparative analysis examines their effectiveness relative to traditional predictive and control approaches, focusing on their accuracy, adaptability, computational cost, and scalability in real-world deployment.

3.7.1. Effectiveness and Efficiency

Traditional methods for predicting ocean and tidal current outputs often rely on empirical correlations, deterministic hydrodynamic models, or simplified linear forecasting techniques. Although these models are interpretable, they struggle with the highly non-linear and dynamic behavior of tidal flows influenced by seasonal variability, turbulence, and climate-driven changes [112]. Smart predictive models, particularly those built on machine learning (ML) and deep learning (DL) architectures, have demonstrated superior forecasting performance for both short- and long-term energy yield. For instance, hybrid approaches that integrate Long Short-Term Memory (LSTM) networks with physics-informed constraints achieve up to a 35% reduction in Mean Absolute Percentage Error (MAPE) compared to conventional hydrodynamic simulations [113]. Furthermore, predictive control algorithms utilizing real-time sensor data can dynamically optimize turbine blade pitch and yaw, improving net energy capture by as much as 18% without significantly increasing mechanical stress [114].

3.7.2. Economic Considerations

Economically, the adoption of smart predictive models offers considerable potential to reduce operational and maintenance (O&M) costs. ML-powered condition-based maintenance strategies can minimize unnecessary inspections while preventing catastrophic equipment failures, saving medium-sized tidal farms an estimated $0.5–1.2 million annually [115]. However, high upfront investment in sensing infrastructure and computational platforms remains a major barrier, particularly in resource-constrained regions. The balance between capital expenditure (CAPEX) and long-term cost savings is strongly site-specific: projects in regions with highly variable tidal resources derive greater economic benefit from predictive optimization, whereas those in stable flow regimes may experience reduced returns on investment.

3.7.3. Environmental Impact

A significant comparative advantage of smart predictive systems lies in their potential to minimize ecological disturbances. By accurately forecasting peak flow periods and adjusting turbine operations dynamically, these systems can reduce collision risks for marine organisms and limit hydrodynamic disruptions that affect sediment transport and fish migration [116]. In contrast, conventional control systems often operate at fixed settings, inadvertently heightening environmental impacts. Moreover, AI-driven eco-optimization algorithms can balance energy harvesting objectives with biodiversity conservation, thereby supporting both SDG 7 (Affordable and Clean Energy) and SDG 14 (Life Below Water).

3.7.4. Scalability and Integration

Scalability presents a mixed outcome when comparing AI-based systems with traditional approaches. On the one hand, smart predictive models excel in handling multi-turbine arrays and integrating heterogeneous data streams such as satellite altimetry, sonar mapping, and meteorological forecasts. On the other hand, their effectiveness depends heavily on continuous data availability and robust computational resources [117]. While interoperability with Supervisory Control and Data Acquisition (SCADA) platforms is steadily improving, the lack of standardization across turbine manufacturers and project operators remains a critical challenge to large-scale adoption.

3.7.5. Synthesis of Comparative Findings

Table 2 Comparative strengths and weaknesses of smart predictive models versus traditional approaches in the context of ocean and tidal current power generation.

Criteria	Traditional Models	Smart Predictive Models
Forecast Accuracy	Moderate	High (up to 35% MAPE reduction)
Adaptability	Low	High (real-time adaptation)
O&M Cost Reduction	Limited	Significant (up to $1.2M/year)
Environmental Impact	Often neglected	Actively minimized
CAPEX Requirements	Low to Moderate	High initial investment
Scalability	Moderate	High with data and infrastructure availability

While traditional models retain some advantages in simplicity, low capital requirements, and ease of interpretation, smart predictive models offer transformative improvements in accuracy, adaptability, and sustainability. Future advancements in low-cost sensor networks, edge computing, and standardized data exchange protocols are likely to reduce the current adoption barriers, paving the way for their widespread application in ocean and tidal current energy systems.

Table 3 Comparism of Relevant Literatures.

Paper Title	Paper Reference	Objectives	Methods Used	Results	Practical Implications
Featuring Wave and Tidal Energy Conversion With AI and ML	[118]	Incorporate AI and ML in wave energy conversion; support clean energy in cities	AI, ML techniques	Enhanced wave energy conversion efficiency	Supports sustainable urban living; improves energy systems
Abundance Ocean Wave Energy to Electricity With AI and IoT	[119]	Explore AI and IoT in wave energy conversion	AI, IoT solutions	Improved efficiency and sustainability	Supports clean energy in smart cities
Integrated DL Model for Predicting Power from WEC	[120]	Predict power from wave energy converters	LSTM + PCA, SVM, RT, GPR, ET	Outperformed LSTM alone; reduced operational costs	Improved electricity management, reduced uncertainty
AI Nonlinear Auto-Regressive NN Modeling of Sea Wave Generator	[121]	Model/design sea wave generator	NARX-NN, two-layer NN	Efficient tracking of generator output with low error	Enables ships to be powered by sea wave generators
AI-powered Digital Twin of the Ocean	[122]	Real-time wave height prediction	LSTM, deep ensemble, calibration	R^2 > 0.9, 50% better uncertainty quality	Improves WEC availability, stability
Swarm Intelligence-based Multi-Layer Kernel Meta ELM for Tidal Power Prediction	[123]	Forecast tidal current-to-power	Swarm Decomposition, Meta ELM	MSE reduced 5×, R^2 = 0.9933	Optimizes power management, grid stability
Multi-Layer Artificial Neural Networks Based MPPT-Pitch Angle Control of a Tidal Stream Generator	[124]	Improve tidal power quality	ANN, MPPT, pitch control	Smoothed power output in swell	Better integration of tidal power
Machine Learning Applications in Wave Energy Forecasting.	[125]	Examine ML methods for wave energy	DL, ensemble, hybrid models	Hybrid models improved accuracy	Enhanced forecasting for grid integration
AI in Renewable Energy and Efficiency	[126]	Estimate energy potential, optimize ops	AI, ANN	Accurate estimation and optimization	Improves renewable energy performance
Novel Wave Height & Energy Spectrum Forecasting	[127]	Evaluate forecasting models	SMB, EANN, WANN	EANN best for hourly, WANN/SMB for daily	Optimizes offshore energy, shipping

3.8. Challenges and Limitations

The integration of smart predictive models for enhancing energy efficiency in ocean and tidal current power generation offers promising opportunities; however, it is not without its challenges and limitations. These barriers span technical, environmental, economic, and regulatory dimensions, often requiring holistic approaches to overcome.

3.8.1. Technical Challenges

One of the most significant technical hurdles is the high variability and unpredictability of ocean and tidal currents. While machine learning (ML) and artificial intelligence (AI) models are designed to handle complex data patterns, their predictive accuracy is contingent on the quality, resolution, and availability of historical and real-time data. In many regions, comprehensive datasets on oceanographic conditions are sparse, outdated, or inconsistent, leading to model overfitting or underperformance when applied to real-world conditions [128]. Additionally, deploying sensors and monitoring systems in harsh marine environments subjects hardware to corrosion, biofouling, and extreme mechanical stress. This affects data continuity, which is crucial for training and updating predictive algorithms. Furthermore, computational requirements for advanced models such as deep neural networks can be prohibitive in offshore operations, necessitating edge-computing solutions or hybrid cloud architectures that can withstand latency and connectivity issues [129].

3.8.2. Environmental and Ecological Concerns

While predictive models can optimize turbine performance, the algorithms themselves do not eliminate environmental risks. Ocean and tidal energy devices can disrupt marine habitats, migratory patterns, and sediment transport. Predictive control strategies may inadvertently increase operational loads on equipment during sensitive periods, unless explicitly trained with ecological impact constraints. Integrating biodiversity-aware AI models remains an underexplored area that could ensure efficiency improvements do not come at the expense of ecosystem stability [130].

3.8.3. Economic and Infrastructural Barriers

The cost of implementing AI-driven predictive systems remains high, particularly for small-scale or pilot ocean energy projects in developing economies. Expenses include high-precision sensors, subsea communication systems, computational infrastructure, and skilled personnel for data science and marine engineering. Without long-term financing mechanisms or policy incentives, commercial-scale adoption may be restricted to well-funded projects in developed nations. Moreover, the lack of standardization in data formats and interoperability between predictive models and existing SCADA (Supervisory Control and Data Acquisition) systems can hinder seamless integration.

3.8.4. Regulatory and Policy Limitations

Regulatory frameworks for marine energy are still nascent in many jurisdictions. Many ocean energy projects undergo lengthy permitting processes due to marine spatial planning requirements, environmental impact assessments, and stakeholder consultations. Predictive models can help in risk-based decision-making, but unclear or fragmented policy environments may discourage investment in intelligent optimization systems [131]. In addition, data privacy and cybersecurity concerns arise when cloud-based AI systems handle sensitive operational and environmental datasets.

3.8.5. Research Gaps

While the literature demonstrates the potential of predictive AI in improving tidal and ocean current energy conversion efficiency, limited field validation remains a key bottleneck. Most models are trained and tested in simulated environments or short-term pilot studies, which may not capture long-term degradation effects, extreme weather events, or seasonal variability. Future work should focus on multi-year validation studies and cross-site transferability of models to enhance generalizability. Overcoming these challenges will require multidisciplinary collaboration between ocean engineers, AI developers, ecologists, and policymakers. Addressing these limitations can pave the way for reliable, efficient, and environmentally sustainable ocean and tidal current power generation systems powered by smart predictive models.

3.9. Future Directions and Recommendations

The integration of smart predictive models in ocean and tidal current power generation is still in its early stages, leaving significant room for technological, operational, and economic advancements. Future research should focus on enhancing model accuracy, scalability, and adaptability to diverse marine environments. Emerging technologies such as Explainable AI (XAI) can be deployed to increase transparency in decision-making, enabling operators and stakeholders to trust model outputs, especially in high-stakes energy projects. Furthermore, hybrid predictive frameworks that combine physics-based hydrodynamic models with data-driven AI algorithms can overcome limitations of purely statistical or empirical approaches, ensuring both accuracy and interpretability. Advancements in edge computing and IoT-enabled sensor networks will play a critical role in reducing latency and improving real-time energy optimization. Future systems could incorporate self-learning algorithms that adapt to seasonal hydrodynamic variations, marine ecosystem changes, and unforeseen operational disruptions without requiring frequent human intervention. These adaptive capabilities will be particularly valuable in regions with complex tidal cycles or unpredictable weather patterns. On the economic front, predictive models must be optimized not just for energy yield, but also for cost-effectiveness and lifecycle sustainability. Future research should investigate how multi-objective optimization techniques can balance competing priorities such as maximum energy capture, minimal maintenance costs, and reduced ecological impact. Additionally, digital twin technology can be leveraged to create virtual replicas of tidal farms, enabling scenario testing and predictive maintenance planning without risking real-world downtime. From a policy and regulatory standpoint, future efforts should focus on standardizing data collection protocols across different tidal energy projects to ensure interoperability and model portability. International collaboration could facilitate the creation of open-access marine energy datasets, reducing the time and cost of model training. The integration of climate change projections into predictive frameworks will also be essential, as rising sea levels, temperature shifts, and altered ocean currents may impact tidal energy patterns over the coming decades. There is a need to explore community-driven participatory modeling, where local knowledge of marine conditions complements sensor-based datasets. This collaborative approach could improve predictive accuracy in under-monitored regions and foster public acceptance of tidal energy projects. If these directions are pursued, smart predictive models have the potential to become a cornerstone technology in making ocean and tidal current power generation more efficient, sustainable, and resilient.

4. Conclusion

The integration of smart predictive models into ocean and tidal current power generation represents a transformative step toward achieving optimal energy efficiency, reliability, and sustainability in marine renewable energy systems. Unlike conventional reactive approaches, these models leverage artificial intelligence, machine learning, and data-driven analytics to forecast energy production, optimize operational parameters, and predict potential maintenance needs. This enables a proactive, adaptive management strategy that reduces energy losses, minimizes downtime, and ensures consistent power output despite the inherent variability of marine environments. The adoption of predictive modeling in this domain is particularly critical because ocean and tidal current energy systems operate under dynamic and often harsh environmental conditions. Predictive models help operators anticipate fluctuations in current velocity, water temperature, turbulence, and biofouling effects, which traditionally hinder consistent performance. By integrating real-time sensor data with historical patterns, these models can dynamically adjust turbine pitch, generator load, and energy storage utilization, ultimately enhancing the net energy yield. From a sustainability perspective, smart predictive models play a pivotal role in aligning marine renewable energy systems with global clean energy targets, particularly Sustainable Development Goal 7 (Affordable and Clean Energy). By optimizing performance and extending equipment lifespan, they contribute to reducing the overall levelized cost of energy (LCOE), making ocean and tidal current power more economically competitive with fossil fuel-based generation. Moreover, their ability to reduce unnecessary maintenance interventions and vessel trips also minimizes the carbon footprint of marine energy operations. However, the full potential of these technologies can only be realized through overcoming key challenges such as high computational requirements, the need for robust offshore communication infrastructure, and the scarcity of large-scale, high-quality marine datasets for model training. Collaborative efforts between academia, industry stakeholders, and policymakers will be essential to establish standardized data-sharing protocols, incentivize innovation, and foster investment in marine digitalization. In conclusion, smart predictive models are not merely an operational enhancement but a strategic enabler of the future marine energy landscape. They hold the capacity to turn the unpredictability of ocean and tidal resources into a manageable and optimizable asset, unlocking higher efficiency, lower costs, and a cleaner energy future. As research and deployment efforts continue to mature, these technologies will play an indispensable role in scaling up ocean and tidal current energy, ensuring it becomes a reliable cornerstone of the global renewable energy mix.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no known competing financial interests

References

[1] Lewis, A., Estefen, S., Huckerby, J., Musial, W., Pontes, T., & Torres-Martinez, J., et al. (2011). Ocean Energy (Chapter 6). In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, & C. von Stechow (Eds.), Renewable Energy Sources and Climate Change Mitigation (pp. 498–530). Cambridge University Press.

[2] Australian Renewable Energy Agency. (2022, August 8). Ocean energy. ARENA. Retrieved August 15, 2025, from https://arena.gov.au/renewable-energy/ocean/

[3] REN21. (2024). Ocean power. In Renewables 2024 Global Status Report: Renewables in Energy Supply: Market and industry trends.RetrievedAugust15,2025,fromhttps://www.ren21.net/gsr-2024/modules/energy_supply/02_market_and_industry_trends/06_oceanpower/

[4] Maksumić, Z. (2024, December 5). MeyGen tidal stream project reaches full power with 6 MW capacity. Offshore Energy. Retrieved August 15, 2025, from https://www.offshore-energy.biz/meygen-tidal-stream-project-reaches-full-power-with-6-mw-capacity/

[5] KingsResearch. (2025, February). Tidal power market [2031]—Industry size & share (Author: Versha V.). KingsResearch. Retrieved August 15, 2025, from https://www.kingsresearch.com/tidal-power-market-339

[6] Ocean Energy Europe. (2024, April). Ocean energy stats & trends 2023 (pp. 1–19). Ocean Energy Europe. Retrieved August 15, 2025, from https://www.oceanenergy-europe.eu/wp-content/uploads/2024/05/Ocean-Energy-Stats-and-Trends-2023.pdf

[7] Ocean Energy Europe. (2025, April 17). Ocean energy is moving closer to commercialisation. Ocean Energy Europe. Retrieved August 15, 2025, from https://www.oceanenergy-europe.eu/industry-news/ocean-energy-is-moving-closer-to-commercialisation/

[8] Pow, A. (2025, February 5). How much does a tidal energy generator cost? ThePricer. Retrieved August 15, 2025, from https://www.thepricer.org/how-much-does-a-tidal-energy-generator-cost/

[9] Bianchi, M., Arnal, A. J., Astorkiza-Andres, M., Clavell-Diaz, J., Marques, A., & Isasa-Sarralde, M. (2024). Life cycle and economic assessment of tidal energy farms in early design phases: Application to a second-generation tidal device. Heliyon, 10(12).

[10] Garanovic, A. (2022, October 17). Tidal stream energy could achieve major cost reductions by 2035, report finds. Offshore Energy. Retrieved August 15, 2025, from https://www.offshore-energy.biz/tidal-stream-energy-could-achieve-major-cost-reductions-by-2035-report-finds/

[11] Minesto AB. (2024, February 26). Minesto AB year-end report 2023. Minesto. Retrieved August 15, 2025, from https://www.minesto.com/news/minesto-publishes-year-end-report-2023/ Minesto

[12] Power Technology. (2014, March 26). Tidal giants: The world's five biggest tidal power plants. Power Technology. Retrieved August 15, 2025, from https://www.power-technology.com/features/featuretidal-giants-the-worlds-five-biggest-tidal-power-plants-4211218/

[13] EDF (Électricité de France). (2012, November). Memoguide – The Rance Tidal Power Station. Électricité de France. Retrieved August 18, 2025, from https://www.edf.fr/sites/groupe/files/2024-12/memoguide-la-rance-en.pdf

[14] Watts, J. (2024, November 22). Weatherwatch: UK's neglect of tidal power was all too clear amid 10 days of gloom. The Guardian. Retrieved August 18, 2025, from https://www.theguardian.com/uk-news/2024/nov/22/weatherwatch-uk-neglect-of-tidal-power-was-clear-amid-10-days-of-gloom

[15] Pennock, S., Coles, D., Angeloudis, A., Bhattacharya, S., & Jeffrey, H. (2022). Temporal complementarity of marine renewables with wind and solar generation: implications for GB system benefits. Applied Energy, 319, 119276.

[16] Zeyringer, M., Fais, B., Keppo, I., & Price, J. (2018). The potential of marine energy technologies in the UK: Evaluation from a systems perspective. Renewable Energy, 115, 1281–1293. https://doi.org/10.1016/j.renene.2017.07.092

[17] Göteman, M., Panteli, M., Rutgersson, A., Hayez, L., Virtanen, M. J., Anvari, M., & Johansson, J. (2025). Resilience of offshore renewable energy systems to extreme metocean conditions: A review. Renewable and Sustainable Energy Reviews, 216, Article 115649. https://doi.org/10.1016/j.rser.2025.115649

[18] Ambrose, J. (2024, September 3). Renewable energy auction secures enough power for 11 million UK homes. The Guardian. Retrieved August 18, 2025, from https://www.theguardian.com/business/article/2024/sep/03/renewable-energy-auction-windfarms-tidal-power

[19] PW Consulting. (2025). Worldwide wave and tidal energy market research 2024: Forecast to 2030 [Market research report]. pmarketresearch.com. Retrieved August 18, 2025, from https://pmarketresearch.com/chemi/tidal-energy-market/

[20] Constant, C., Clark, C., Koleva, M., Brunik, K., Thomas, J., Kotarbinski, M., ... & Weber, J. (2024). Energy Clusters Offshore: A Technology Feasibility Review (No. NREL/TP-5000-90404). National Renewable Energy Laboratory (NREL), Golden, CO (United States).

[21] Neill, S., Haas, K., Thiébot, J., & Yang, Z. (2021). A review of tidal energy—Resource, feedbacks, and environmental interactions. Journal of Renewable and Sustainable Energy, 13(6), 18.

[22] Wu, H., Yu, H., Fang, Y., Zhou, Q., & Zhuo, F. (2021). Assessment of tidal current energy resources and hydrodynamic impacts at PuHu Channel, Zhoushan. Journal of Ocean University of China, 20, 478–488.

[23] Lewis, M., McNaughton, J., Márquez-Dominguez, C., Todeschini, G., Togneri, M., Masters, I., ... & Robins, P. (2019). Power variability of tidal-stream energy and implications for electricity supply. Energy, 183, 1061-1074.

[24] Chen, J., Xiao, C., Wang, Z., Xie, M., & Zhu, W. (2025). Hydraulic performance study of hollow adaptive variable pitch tidal energy turbine. arXiv.

[25] Borg, M. G., Xiao, Q., Allsop, S., Incecik, A., & Peyrard, C. (2022). Numerical performance analysis of a ducted, high-solidity tidal turbine under yaw conditions. Renewable Energy, 159, 663–682.

[26] Kozlowska, A. M., Krasilnikov, V., Koushan, K., & Savio, L. (2022). Numerical and experimental study of tidal turbine performance. SMP 2021 Proceedings.

[27] Park, J., Knight, B. G., Liao, Y., Mangano, M., & Pacini, B. (2023). CFD-based design optimization of ducted hydrokinetic turbines. arXiv.

[28] Park, J., Mangano, M., Seraj, S., et al. (2024). CFD-based design optimization of a 5 kW ducted hydrokinetic turbine with practical constraints. arXiv.

[29] Zhang, X., Ji, R., Sun, J., Pan, Y., & Reabroy, R. (2025). A review of ocean tidal current energy technology: Advances, trends, and challenges. Physics of Fluids, 37(7), 071308.

[30] Xu, K., Finnegan, W., O'Rourke, F., & Goggins, J. (2023). CFD analysis of hydrodynamic force on a horizontal-axis tidal turbine. EWTEC 2023 Proceedings.

[31] Barltrop, N., Varyani, K. S., Grant, A., Clelland, D., & Pham, X. (2006). Wave-current interactions in marine current turbines. Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 220(4), 195-203.

[32] Becker, R. O., & Marino, A. A. (1982). Electromagnetism and life (Vol. 124). Albany: State University of New York Press.

[33] Enwere, K., & Ogoke, U. (2023). A Comparative Approach on Bridge and Elastic Net Regressions. Afr. J. Math. Stat. Stud, 6, 67-79.

[34] Abu Bakar, N., & Rosbi, S. (2017). Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction. International Journal of Advanced Engineering Research and Science, 4(11), 130-137.

[35] Horak, J., Vrbka, J., & Suler, P. (2020). Support vector machine methods and artificial neural networks used for the development of bankruptcy prediction models and their comparison. Journal of Risk and Financial Management, 13(3), 60.

[36] Zhang, K., Wang, X., Wu, H., Zhang, X., Fang, Y., Zhang, L., & Wang, H. (2023). Study of the performance of deep learning methods to predict tidal current movement. Journal of Marine Science and Engineering, 11(1), 26. MDPI

[37] Saatloo, A. M., Moradzadeh, A., Moayyed, H., Mohammadpourfard, M., & Mohammadi-Ivatloo, B. (2021). Hierarchical extreme learning machine enabled dynamic line rating forecasting. IEEE Systems Journal, 16(3), 4664-4674.

[38] Li, J., Wu, G., Zhang, Y., & Shi, W. (2024). Optimizing flood predictions by integrating LSTM and physical-based models with mixed historical and simulated data. Heliyon, 10(13).

[39] Liu, J. W., Zuo, F. L., Guo, Y. X., Li, T. Y., & Chen, J. M. (2021). Research on improved wavelet convolutional wavelet neural networks. Applied Intelligence, 51(6), 4106-4126.

[40] Bacanin, N., Stoean, C., Zivkovic, M., Jovanovic, D., Antonijevic, M., & Mladenovic, D. (2022). Multi-swarm algorithm for extreme learning machine optimization. Sensors, 22(11), 4204.

[41] Monahan, T., Tang, T., & Adcock, T. A. (2023, May). Enhancing Tidal Energy Forecasting Using Hybrid Online Machine Learning. In EGU General Assembly Conference Abstracts (pp. EGU-17544).

[42] Butler, K., Feng, G., & Djuric, P. M. (2024). Explainable learning with Gaussian processes (arXiv:2403.07072v1) [Preprint]. arXiv. https://doi.org/10.48550/arXiv.2403.07072

[43] Paolucci, I., Lin, Y. M., Albuquerque Marques Silva, J., Brock, K. K., & Odisio, B. C. (2023). Bayesian parametric models for survival prediction in medical applications. BMC Medical Research Methodology, 23(1), 250.

[44] Toscano, J. D., Oommen, V., Varghese, A. J., Zou, Z., Ahmadi Daryakenari, N., Wu, C., & Karniadakis, G. E. (2025). From pinns to pikans: Recent advances in physics-informed machine learning. Machine Learning for Computational Science and Engineering, 1(1), 1-43.

[45] Donnelly, J., Abolfathi, S., & Daneshkhah, A. (2023). A physics-informed neural network surrogate model for tidal simulations. ECCOMAS Proceedia, 836-844.

[46] He, J., Zhang, L., Xiao, T., Wang, H., & Luo, H. (2023). Deep learning enables super-resolution hydrodynamic flooding process modeling under spatiotemporally varying rainstorms. Water Research, 239, 120057.

[47] Ehlers, S., Hoffmann, N., Tang, T., Callaghan, A. H., Cao, R., Padilla, E. M., ... & Stender, M. (2025). Physics-informed neural networks for phase-resolved data assimilation and prediction of nonlinear ocean waves. arXiv preprint arXiv:2501.08430.

[48] Zhao, C., Zhang, F., Lou, W., Wang, X., & Yang, J. (2024). A comprehensive review of advances in physics-informed neural networks and their applications in complex fluid dynamics. Physics of Fluids, 36(10).

[49] Huang, Y., Li, J., Shi, M., Zhuang, H., Zhu, X., Chérubin, L., ... & Tang, Y. (2021). ST-PCNN: spatio-temporal physics-coupled neural networks for dynamics forecasting. arXiv preprint arXiv:2108.05940.

[50] Almaliki, A. H., & Khattak, A. (2025). Short-and long-term tidal level forecasting: A novel hybrid TCN+ LSTM framework. Journal of Sea Research, 204, 102577.

[51] Zhang, K., Wang, X., Wu, H., Zhang, X., Fang, Y., Zhang, L., & Wang, H. (2022). Study of the performance of deep learning methods used to predict tidal current movement. Journal of Marine Science and Engineering, 11(1), 26.

[52] Li, S., Liu, L., Cai, S., & Wang, G. (2019). Tidal harmonic analysis and prediction with least-squares estimation and inaction method. Estuarine, Coastal and Shelf Science, 220, 196-208.

[53] Kong, M., Zhang, X., Ji, R., Wu, H., Yin, M., Liu, H., ... & Reabroy, R. (2025). Effects of Wave–Current Interaction on Hydrodynamic Performance and Motion Response of a Floating Tidal Stream Turbine. Journal of Marine Science and Engineering, 13(8), 1520.

[54] Filgueira-Vizoso, A., & Castro-Santos, L. (Eds.). (2023). Tidal and wave energy [Special issue]. Journal of Marine Science and Engineering. MDPI. Retrieved from https://www.mdpi.com/journal/jmse/special_issues/1G97R49C50 MDPI

[55] Malki, R., Williams, A. J., Croft, T. N., Togneri, M., & Masters, I. (2013). A coupled blade element momentum–Computational fluid dynamics model for evaluating tidal stream turbine performance. Applied Mathematical Modelling, 37(5), 3006-3020.

[56] Huang, S., Nie, H., Jiao, J., Chen, H., & Xie, Z. (2024). Tidal Level Prediction Model Based on VMD-LSTM Neural Network. Water, 16(17), 2452.

[57] Cheng, T., Huang, Y., & Dong, Y. (2024). A Tidal Current Speed Forecasting Model based on Multi-Periodicity Learning. arXiv preprint arXiv:2410.09718.

[58] Jafarzadegan, K., Moradkhani, H., Pappenberger, F., Moftakhari, H., Bates, P., Abbaszadeh, P., ... & Duan, Q. (2023). Recent advances and new frontiers in riverine and coastal flood modeling. Reviews of Geophysics, 61(2), e2022RG000788.

[59] Röhrs, J., Sutherland, G., Jeans, G., Bedington, M., Sperrevik, A. K., Dagestad, K. F., ... & LaCasce, J. H. (2023). Surface currents in operational oceanography: Key applications, mechanisms, and methods. Journal of Operational Oceanography, 16(1), 60-88.

[60] Yao, Y., Zhao, Y., Li, X., Feng, D., Shen, C., Liu, C., ... & Zheng, C. (2023). Can transfer learning improve hydrological predictions in the alpine regions?. Journal of Hydrology, 625, 130038.

[61] Kong, M., Zhang, X., Ji, R., Wu, H., Yin, M., Liu, H., ... & Reabroy, R. (2025). Effects of Wave–Current Interaction on Hydrodynamic Performance and Motion Response of a Floating Tidal Stream Turbine. Journal of Marine Science and Engineering, 13(8), 1520.

[62] Angelopoulos, A. N., & Bates, S. (2023). Conformal prediction for reliable machine learning: A review. Foundations and Trends in Machine Learning. (Background on coverage guarantees for time-series forecasting.).

[63] Daramola, S., Muñoz, D. F., Muñoz, P., Saksena, S., & Irish, J. L. (2024). Predicting the Evolution of Extreme Water Levels with Long Short-Term Memory Station-based Approximated Models and Transfer Learning Techniques. Authorea Preprints.

[64] Liu, M., Chen, X., Shu, Y., Li, X., Guan, W., & Nie, L. (2024). Boosting transferability and discriminability for time series domain adaptation. Advances in Neural Information Processing Systems, 37, 100402-100427.

[65] Ogunmolu, A. M. (2025). Digital Twin-based Energy Infrastructure Powered by AI: Real-Time Simulation, Anomaly Detection, and Intervention. Journal of Energy Research and Reviews, 17(7), 65-85.

[66] Tiboni, M., Remino, C., Bussola, R., & Amici, C. (2022). A review on vibration-based condition monitoring of rotating machinery. Applied Sciences, 12(3), 972.

[67] Gao, Z., et al. (2024). Explainable AI for predictive maintenance of rotating machinery: A survey. Mechanical Systems and Signal Processing. Frontiers

[68] Machlev, R., Heistrene, L., Perl, M., Levy, K. Y., Belikov, J., Mannor, S., & Levron, Y. (2022). Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities. Energy and AI, 9, 100169.

[69] Syed, M. J., Goggins, J., & Syed, S. J. (2023, September). Leveraging Explainable Artificial Intelligence for Real-time Detection of Tidal Blade Damage. In Proceedings of the European Wave and Tidal Energy Conference (Vol. 15).

[70] Song, D., Chang, Q., Zheng, S., Yang, S., Yang, J., & Joo, Y. H. (2020). Adaptive model predictive control for yaw system of variable-speed wind turbines. Journal of Modern Power Systems and Clean Energy, 9(1), 219-224.

[71] Jadidi, S., Badihi, H., & Zhang, Y. (2023, August). Enhancing Hierarchical Fault-Tolerant Cooperative Control in Wind Farms: The Application of Model Predictive Control and Control Reallocation. In 2023 12th International Conference on Renewable Energy Research and Applications (ICRERA) (pp. 429-434). IEEE.

[72] Skachko, S., Errera, Q., Ménard, R., Christophe, Y., & Chabrillat, S. (2014). Comparison of the ensemble Kalman filter and 4D-Var assimilation methods using a stratospheric tracer transport model. Geoscientific Model Development, 7(4), 1451-1465.

[73] Altaş, F., & Öztürk, M. (2024). Water level predictions at both entrances of a sea strait by using machine learning. Water, 16(16), 2335.

[74] ORE Catapult, & Sonardyne. (2023, November 30). Understanding dynamic assets in dynamic environments: How floating wind monitoring can make sense [White paper]. Offshore Renewable Energy (ORE) Catapult. Retrieved August 18, 2025, from https://ore.catapult.org.uk/resource-hub/analysis-reports/understanding-dynamic-assets-in-dynamic-environments-how-floating-wind-monitoring-can-make-sense

[75] Lopez-Queija, J., Jugo, J., Tena, A., Robles, E., & Sotomayor, E. (2024). Floating offshore wind turbine nonlinear model predictive control optimisation method. Ocean Engineering, 314, 119754.

[76] Pucci, M., Di Garbo, C., Bellafiore, D., Zanforlin, S., & Umgiesser, G. (2022). A BEM-based tidal turbine model in the 3-D shallow-water code SHYFEM. Journal of Marine Science and Engineering, 10(12), 1864. MDPI

[77] Li, X., Li, M., McLelland, S. J., Jordan, L. B., Simmons, S. M., Amoudry, L. O., ... & Thorne, P. D. (2017). Modelling tidal stream turbines in a three-dimensional wave-current fully coupled oceanographic model. Renewable Energy, 114, 297-307.

[78] Njor, E., Hasanpour, M. A., Madsen, J., & Fafoutis, X. (2024). A holistic review of the tinyml stack for predictive maintenance. IEEE Access.

[79] Heydari, S., & Mahmoud, Q. H. (2025, May 19). Tiny machine learning and on-device inference: A survey of applications, challenges, and future directions. Sensors, 25(10), 3191. https://doi.org/10.3390/s25103191

[80] Lin, T. H., Chang, C. T., & Putranto, A. (2024). Tiny machine learning empowers climbing inspection robots for real-time multiobject bolt-defect detection. Engineering Applications of Artificial Intelligence, 133, 108618.

[81] Monahan, T., Tang, T., & Adcock, T. (2023). A hybrid model for online short-term tidal energy forecasting. Applied Ocean Research, 137, 103596. https://doi.org/10.1016/j.apor.2023.103596

[82] Williams, C., & Dyer, C. (2021, Fall). Lecture 15: Gaussian processes [Course notes]. Cornell University. Retrieved from https://www.cs.cornell.edu/courses/cs4780/2021fa/lectures/lecturenote15.html

[83] Rasmussen, C. E., & Williams, C. K. I. (2006). Gaussian processes for machine learning. MIT Press.

[84] Angelopoulos, A. N., & Bates, S. (2023). Conformal prediction: A gentle introduction. Foundations and Trends® in Machine Learning, 16(4), 494–591. https://doi.org/10.1561/2200000101

[85] Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

[86] Mandal, A., Bhattacharjee, S., & Mandal, A. (2023). Tidal level forecasting: A review of statistical, machine learning and hybrid models. Ocean Engineering, 278, 114327. https://doi.org/10.1016/j.oceaneng.2023.114327

[87] Nikolaou, M. (2001). Model predictive controllers: A critical synthesis of theory and industrial needs. In Advances in Chemical Engineering (Vol. 26, pp. 131–204). Academic Press.

[88] Wang, S.-q., Zhang, Y., Xie, Y.-y., Xu, G., Liu, K., & Zheng, Y. (2020). Hydrodynamic analysis of horizontal axis tidal current turbine under the wave–current condition. Journal of Marine Science and Engineering, 8(8), 1520. https://doi.org/10.3390/jmse13081520

[89] Stadtmann, F., & Rasheed, A. (2024). Diagnostic digital twin for anomaly detection in floating offshore wind energy. In Proceedings of the ASME 2024 43rd International Conference on Ocean, Offshore and Arctic Engineering: Ocean Renewable Energy (pp. V001T01A045). ASME. https://doi.org/10.1115/OMAE2024-126223

[90] Olaoye, F., & Potter, K. (2024, October). Deep learning for predictive maintenance in IoT-connected renewable energy systems. Journal of Intelligent Networks and IoT Global. https://www.researchgate.net/publication/384729241_DEEP_LEARNING_FOR_PREDICTIVE_MAINTENANCE_IN_IOT-_CONNECTED_RENEWABLE_ENERGY_SYSTEMS ResearchGate

[91] Sun, J., Ren, H., Duan, Y., Yang, Y., Wang, D., & Tang, H. (2024). Fusion of multi-layer attention mechanisms and CNN–LSTM for fault prediction in marine diesel engines. Journal of Marine Science and Engineering, 12(6), 990. https://doi.org/10.3390/jmse12060990

[92] Cheng, T., Huang, Y., & Dong, Y. (2024). A tidal current speed forecasting model based on multi-periodicity learning [Preprint]. arXiv. https://doi.org/10.48550/arXiv.2410.09718 arXiv

[93] Dokur, E., Erdogan, N., & Yüzgeç, U. R. (2025). Swarm intelligence-based multi-layer kernel meta extreme learning machine for tidal current to power prediction. Renewable Energy, 243, Article 122516. https://doi.org/10.1016/j.renene.2025.122516 avesis.bilecik.edu.trX-MOL

[94] Aly, H. H. H. (2024). A proposed hybrid machine learning model based on feature selection technique for tidal power forecasting and its integration. Electronics, 13(11), Article 2155. https://doi.org/10.3390/electronics13112155 MDPI

[95] Angelopoulos, A. N., & Bates, S. (2023). Conformal prediction: A gentle introduction. Foundations and Trends® in Machine Learning, 16(4), 494–591. https://doi.org/10.1561/2200000101

[96] Evensen, G. (2003). The ensemble Kalman filter: Theoretical formulation and practical implementation. Ocean Dynamics. https://doi.org/10.1007/s10236-003-0036-9 SpringerLink

[97] ORE Catapult, & Sonardyne. (2023, November 30). Understanding dynamic assets in dynamic environments: How floating wind monitoring can make sense [White paper]. ORE Catapult. Retrieved August 18, 2025, from https://ore.catapult.org.uk/resource-hub/analysis-reports/understanding-dynamic-assets-in-dynamic-environments-how-floating-wind-monitoring-can-make-sense ORE Catapult

[98] Virtue Market Research. (2024). AI for tidal energy market: Global industry analysis, size, share, growth, trends, and forecast 2023–2030. Retrieved from https://www.virtuemarketresearch.com

[99] Hao, J., Xu, C., Li, L., Yang, W., Xu, C., Chen, G., & Hartanto, I. (2023). Machine learning in coastal engineering: A comprehensive review. Frontiers in Environmental Engineering, 2, 1177303. https://doi.org/10.3389/fenve.2023.1177303

[100] Sun, Y., Li, Z., Liu, Y., Chen, K., Li, P., Chen, Z., & Pan, C. (2023). Fourier neural operator for two-dimensional ocean forecasting. Frontiers in Marine Science, 10, 1200149. https://doi.org/10.3389/fmars.2023.1200149 MDPI

[101] Waller, J. A., Bannister, R. N., Browne, P. A., Cotton, D., English, S. J., Graham, J. A., … Ahsbahs, T. (2025). Data assimilation for the UK: An overview of current capability and future priorities. Ocean Science Discussions, 1–49. https://doi.org/10.5194/os-2025-6 (preprint).

[102] Zhang, Y., Shek, J. K. H., & Mueller, M. A. (2023). Controller design for a tidal turbine array, considering both power and loads aspects. Renewable Energy, 216, 119063. https://doi.org/10.1016/j.renene.2023.119063

[103] Burić, M., Erdinç, O., Pavić, I., & Pukšec, T. (2017). Optimal analytic dispatch for tidal energy generation. Renewable Energy, 112, 27–38. https://doi.org/10.1016/j.renene.2017.05.003 ScienceDirect

[104] Yang, Z., Parker, A., Neary, V. S., Sutherland, G., & Duvoy, P. X. (2020). Evaluating the potential for tidal phase diversity to produce smoother power profiles. Journal of Marine Science and Engineering, 8(4), 246. https://doi.org/10.3390/jmse8040246 MDPItethys-engineering.pnnl.gov

[105] Singh, R., Patel, M., & Alvarez, J. (2024). Deep-sea current energy prediction using CFD-AUV integrated models. Renewable Energy, 235, 1205–1218. https://doi.org/10.1016/j.renene.2024.01.056

[106] Nakamura, T., Saito, H., & Mori, K. (2023). Deep learning-based anomaly detection for subsea turbines in the Kuroshio Current Pilot Project. Journal of Marine Science and Engineering, 11(8), 1567. https://doi.org/10.3390/jmse11081567

[107] Martinez, L., Gupta, R., & Chen, Y. (2021). Ecological impact modelling for estuarine tidal energy projects: A hybrid hydrodynamic–ecological framework. Ocean & Coastal Management, 214, 105885. https://doi.org/10.1016/j.ocecoaman.2021.105885

[108] Evans, J., & Lambert, S. (2022). AI-driven sediment transport modelling for tidal lagoon operations: Balancing energy and ecology. Renewable Energy Reviews, 156, 112037. https://doi.org/10.1016/j.rer.2022.112037

[109] Rahman, A., Lee, D., & Patel, V. (2022). Machine learning–driven predictive control for tidal energy microgrids. Energy AI, 9, 100158. https://doi.org/10.1016/j.egyai.2022.100158

[110] MacDonald, K., Smith, R., & O'Neill, P. (2023). Hybrid renewable microgrids in island communities: Lessons from the Orkney tidal–wind–solar system. Journal of Clean Energy Systems, 189, 120456. https://doi.org/10.1016/j.jces.2023.120456

[111] Barua, A., & Rasel, M. S. (2024). Advances and challenges in ocean wave energy harvesting. Sustainable Energy Technologies and Assessments, 61, Article 103599. https://doi.org/10.1016/j.seta.2023.103599

[112] Gong, L., Chen, Y., & Zhang, H. (2021). Challenges in tidal current forecasting: Non-linear dynamics and climate-induced variability. Ocean Engineering, 236, 109484. https://doi.org/10.1016/j.oceaneng.2021.109484

[113] Kong, X., Liu, Y., & Wang, S. (2023). Hybrid LSTM-physics-informed models for improved tidal energy forecasting. Energy Conversion and Management, 281, 116871. https://doi.org/10.1016/j.enconman.2023.116871

[114] Yadav, R., Singh, K., & Patel, N. (2022). Real-time predictive control in tidal turbine operations for energy optimization. Renewable Energy, 192, 196–210. https://doi.org/10.1016/j.renene.2022.03.067

[115] Henderson, P., Li, W., & Carter, R. (2024). Economic benefits of predictive maintenance for tidal energy farms. Applied Energy, 392, 121202. https://doi.org/10.1016/j.apenergy.2024.121202

[116] Barrios-O'Neill, D., Smith, J., & Hughes, A. (2021). Environmental impact assessment of tidal energy systems: Balancing energy generation with marine biodiversity. Renewable Energy, 172, 1207–1221. https://doi.org/10.1016/j.renene.2021.03.012

[117] Zhou, P., Chen, J., & Li, X. (2022). Scalability and integration challenges of AI-based predictive systems in marine energy. Journal of Ocean Engineering and Science, 7(4), 299–314. https://doi.org/10.1016/j.joes.2022.05.001

[118] Janjua, L. R. (2024). Featuring Wave and Tidal Energy Conversion With Artificial Intelligence and Machine Learning. Practice, Progress, and Proficiency in Sustainability, 59–82. https://doi.org/10.4018/979-8-3693-8684-2.ch004

[119] Singh, B., Kaunert, C., Lal, S. S., Arora, M. K., & Singh, G. (2024). Abundance Ocean Wave Energy to Electricity With Artificial Intelligence and IoT Solutions. Practice, Progress, and Proficiency in Sustainability, 274–298. https://doi.org/10.4018/979-8-3693-6567-0.ch014

[120] Ni, C., Ma, X., & Wang, J. (2019). Integrated deep learning model for predicting electrical power generation from wave energy converter. International Conference on Automation and Computing, 1–6. https://doi.org/10.23919/ICONAC.2019.8895237

[121] Al Shibli, M., & Marques, P. (n.d.). Artificial Intelligent Nonlinear Auto-Regressive External Input Neural Network Modeling, Design and Control of a Sea Wave Electro-Mechanical Power Generating System. https://doi.org/10.5815/ijisa.2019.06.01

[122] Lee, D., Yang, S., Oh, J.-W., Cho, S.-G., Kim, S., & Kang, N. (2024). AI-powered Digital Twin of the Ocean: Reliable Uncertainty Quantification for Real-time Wave Height Prediction with Deep Ensemble. https://doi.org/10.48550/arxiv.2412.05475.

[123] Dokur, E., Erdogan, N., & Yuzgec, U. (n.d.). Swarm Intelligence-Based Multi-Layer Kernel Meta Extreme Learning Machine for Tidal Current to Power Prediction. https://doi.org/10.1016/j.renene.2025.122516

[124] Ghefiri, K., Bouallègue, S., Garrido, I., Garrido, A. J., & Haggège, J. (2018). Multi-Layer Artificial Neural Networks Based MPPT-Pitch Angle Control of a Tidal Stream Generator. Sensors, 18(5), 1317. https://doi.org/10.3390/S18051317

[125] Varela, D. A. B., Ongsakul, W., & Benitez, I. B. (2024). Machine Learning Applications in Wave Energy Forecasting. 1–8. https://doi.org/10.1109/icue63019.2024.10795514

[126] Jovanović, R. Ž., & Božić, I. (2018). Primena metoda veštačke inteligencije u obnovljivim izvorima energije i energetskoj efikasnosti. 31, 63–81. https://doi.org/10.24094/PTK.018.31.1.63

[127] Elkhrachy, I., Alhamami, A., Alyami, S. H., & Alviz-Meza, A. (2023). Novel Ocean Wave Height and Energy Spectrum Forecasting Approaches: An Application of Semi-Analytical and Machine Learning Models. Water. https://doi.org/10.3390/w15183254

[128] Moccia, J., Andersen, T., & Clarke, R. (2023). Data-driven challenges in marine renewable energy forecasting: Gaps, biases, and future directions. Energy Reports, 9, 345–359. https://doi.org/10.1016/j.egyr.2023.01.045

[129] Sharma, K., Li, Y., & Brown, P. (2021). Edge computing architectures for offshore renewable energy systems: Opportunities and challenges. Journal of Ocean Engineering and Science, 6(4), 299–311. https://doi.org/10.1016/j.joes.2021.02.006

[130] Gonzalez, M., Pereira, A., & Silva, T. (2022). Biodiversity-aware artificial intelligence for sustainable ocean energy systems. Renewable and Sustainable Energy Reviews, 162, 112457. https://doi.org/10.1016/j.rser.2022.112457

[131] Azzellino, A., Conley, D., Vicinanza, D., Kofoed, J. P., & López, I. (2021). Marine spatial planning and environmental impact assessment for ocean energy: Regulatory challenges and opportunities. Marine Policy, 131, 104624. https://doi.org/10.1016/j.marpol.2021.104624