Journal of
Marine Science and Engineering

MDPI

Review

A Review on Machine Learning and Bioinformatics to Study Biofouling in Marine Renewable Energy Devices: Modeling, Performance Prediction, and Maintenance Planning

Shah Dad Hasil [1,†], Zahid Zahid [2,†], Constantine Michailides [3,*], Wei Shi [4,5] and Feroz Irshad [6]

[1] School of Computer Science and Engineering, University of Electronic Science and Technology of China (UESTC), Chengdu 611731, China; shahdad@std.uestc.edu.cn
[2] School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China (UESTC), Chengdu 611731, China; zahid@std.uestc.edu.cn
[3] Department of Civil Engineering, International Hellenic University, 57001 Thessaloniki, Greece
[4] State Key Laboratory of Coastal and Offshore Engineering, Dalian University of Technology, Dalian 116024, China
[5] Ningbo Institute, Dalian University of Technology, Ningbo 315000, China
[6] School of Environmental Science and Engineering, Nankai University, Tianjin 300071, China
* Correspondence: cmichailides@ihu.gr
† These authors contributed equally to this work.

Abstract

Marine renewable energy (MRE) systems operate in harsh marine environments where long-term exposure to seawater leads to biofouling, resulting in increased surface roughness, hydrodynamic drag, added mass, structural loading, sensor degradation, and reduced energy production. Despite its significant operational and economic impact, biofouling management in MRE devices has traditionally relied on manual inspections and empirical growth models, which offer limited predictive capability. This review provides a structured, data-centric synthesis of recent advances in machine learning (ML) and bioinformatics approaches for biofouling modeling, performance prediction, and maintenance planning in offshore wind turbines, tidal turbines, and wave energy converters. The study systematically examines key fouling locations and associated engineering impacts, and analyzes the major data streams used for predictive modeling, including SCADA and condition-monitoring time series, metocean variables, inspection imagery, laboratory and field experiments, and environmental DNA (eDNA) sequencing outputs. We compare modeling strategies ranging from physics-based simulations to classical ML, deep learning, computer vision, and hybrid physics-informed frameworks, and discuss how biological indicators such as microbial community profiles and eDNA-derived taxa abundances can be integrated as predictive features. The review further outlines emerging digital twin architectures for fouling-aware performance forecasting and maintenance decision support. Finally, we identify key challenges including data scarcity, cross-site generalization, validation practices, and uncertainty quantification, and propose future research directions toward integrated, proactive biofouling management systems in marine renewable energy infrastructure.

Keywords: biofouling; marine renewable energy; SCADA; machine learning; bioinformatics; predictive maintenance; environmental DNA; digital twin; tidal turbine; offshore wind

Check for updates

Academic Editor: Nick Aldred

Received: 20 January 2026
Revised: 8 March 2026
Accepted: 11 March 2026
Published: 15 March 2026

1. Introduction

Marine renewable energy, also known as ocean energy, refers to the generation of energy from the movement of seawater, including tides, waves, and ocean currents, as well as from temperature and salinity gradients in the oceans. MRE technologies are designed to capture this energy and convert it into electricity, contributing to a more sustainable energy mix. MRE devices operate reliably over long periods of time in the harsh marine environment. Such devices include tidal turbines, wave energy converters and offshore wind structures, etc. A major challenge on their performance and durability is marine biofouling. Biofouling is the buildup of organisms (algae, barnacles, mussels, etc.) on submerged surfaces [1]. Biofouling causes an increase in surface roughness, weight and drag, causing a decrease in energy output and an increase in stresses on structures [1]. It can lead to sensor impairment and increased corrosion through microbiologically influenced, increasing maintenance costs [1,2].

Traditional methods for controlling biofouling in the marine engineering sector have been based on periodic manual inspection, empirical models for fouling growth, and fouling protective coatings. However, these methods often fall short in level of accuracy or efficiency [2]. In the past few years, the MRE industry has become aware of the need for data-driven, automated methods for monitoring and predicting the impact of biofouling [1,2]. Machine learning (ML) and bioinformatics provide promising tools for the analysis of large datasets, such as turbine operational data, images and environmental DNA for predicting biofouling. Such as [3] used an ML ensemble model for tidal turbine fouling prediction and detection. Likewise, Poozesh et al. (2025) emphasized emerging "AI-driven monitoring systems" as a prospective solution to long-term biofouling management on offshore structures [1].

In another work, Yang et al. (2024) provided a relevant case where bioinformatics and machine learning are integrated with environmental DNA (eDNA) analysis to monitor marine environments, which can be conceptually linked to biofouling monitoring frameworks [4]. They showed how artificial intelligence-assisted environmental DNA metabarcoding combined with high-resolution imaging can improve automated and data-driven monitoring of complex marine ecosystems including detecting species and changes relevant to management and potentially biofouling risk using large molecular datasets and learning models [4,5].

1.1. Scope

In this work we attempt to provide an overview of the current state of the art of the application of ML and bioinformatics methods to biofouling in MRE devices, focusing specifically on the modeling of fouling growth, the prediction of performance losses, and the optimization of maintenance planning. We focus on developments from the last five years (2020 onward), both engineering data-driven models and biological data such as environmental DNA analyses, etc. We mainly focus on finding the answers to four questions from the literature: (i) Where and how does biofouling occur on MRE systems? (ii) What are the engineering implications, data sources and modeling approaches used for eradicating biofouling? (iii) How can operational and environment data combined with biological knowledge be used to predict fouling and help make maintenance decisions? (iv) What are the different integrated predictive frameworks and challenges in the field?

Our review follows a data-centric approach, and does not include an in-depth discussion of antifouling coating materials and purely manual control methods, as these are reviewed elsewhere [6,7]. Our intention is to determine current developments and deficits and to recommend future research directions in this interdisciplinary field. Existing reviews cover important components of the broader landscape, including biofouling impacts and mitigation on offshore structures [1,2], antifouling coatings and technologies [6,7], and wind-turbine condition monitoring and offshore wind operation and maintenance planning [8–11]. In parallel, recent bioinformatics work demonstrates how eDNA/metabarcoding and ML can support automated marine monitoring [4,5]. However, these bodies of work are typically not synthesized into a single framework that connects multi-modal engineering data (e.g., SCADA/CMS, metocean, and inspection imagery) *together with* bioinformatics/eDNA indicators for maintenance-oriented prediction and decision support in MRE devices. Table 1 summarizes this gap and clarifies the contribution of this review.

Table 1. Positioning of this review relative to representative prior works (Maint. DS = maintenance decision support).

Prior Review/ Prior Work	Device Focus	Data Types	ML	eDNA	Maint. DS	What This Review Adds
Poozesh et al. (2025) [1]	Offshore wind	Impacts; inspection evidence	Limited	No	Limited	Extends to MRE and links monitoring data to modeling targets and maintenance triggers (performance loss, loads).
Yebra (2004); Chambers (2006) [6,7]	Coatings (general)	Materials/ mitigation	No	No	Indirect	Moves beyond coatings to data-centric prediction and fouling-aware decision support framing.
García Márquez (2012); Tchakoua (2014); Yang (2014) [8,9,11]	Wind CM	SCADA/CMS; vibration; signals	Yes	No	Yes	Transfers CM concepts to biofouling as a degradation mode in MRE and extends to imagery + environmental drivers.
Rinaldi et al. (2021) [10]	Offshore wind O&M	Planning/ logistics	Limited	No	Yes	Connects O&M decision concepts to fouling-aware forecasting, thresholds, and uncertainty.
Yang et al. (2024) [4,5]	Marine monitoring (general)	eDNA/ metabarcoding; imagery	Yes	Yes	No	Brings eDNA indicators into an MRE biofouling + SCADA/imagery predictive maintenance context (data fusion and decision triggers).

1.2. Review Methodology

This review followed a transparent literature identification and selection process, covering information sources, search strategy, eligibility criteria, selection process, and synthesis approach. We applied a simple quality checklist to contextualize the strength of evidence in included studies, focusing on ML validation risks (e.g., leakage control and benchmarking) and on eDNA/bioinformatics reporting (e.g., pipeline transparency, controls, and normalization), and we used these checks to qualify the synthesis rather than to exclude studies. For each included study, checklist items were recorded as Yes/Partial/No (or equivalent notes) and were summarized narratively to indicate where evidence was stronger (e.g., leakage-aware validation and baselines) or weaker (e.g., limited pipeline/control reporting), without excluding studies on this basis. The search began on 2 December 2025 and was last updated on 7 January 2026. We searched Scopus, Web of Science Core Collection, and IEEE Xplore to capture interdisciplinary work across marine energy engineering, offshore operations, and data-driven modeling [12,13]. To minimize omissions, we also conducted backward reference checks of key included papers and relevant recent reviews, and forward citation checks of highly central papers, where possible.

The search strategy combined three concept blocks: (1) biofouling terms (e.g., biofouling, marine growth, biofilm, microfouling, and macrofouling), (2) MRE context terms (e.g., tidal turbines, wave energy converters, offshore/floating wind, and multipurpose offshore structures), and (3) modeling/analytics terms (e.g., machine learning, computer vision, time series/SCADA, condition monitoring, CFD/FSI, digital twins, physics-informed modeling, and eDNA/metabarcoding) [8,9]. The complete database-specific search strings (exact syntax and fields) are reported in Table 2. For readability, the core representative query was

> (biofoul* OR "marine growth" OR biofilm OR barnacle* OR algae OR microfoul* OR macrofoul*) AND ("marine renewable energy" OR "marine energy" OR tidal OR "tidal turbine" OR "wave energy converter" OR OWC OR "offshore wind" OR "floating wind" OR OTEC OR "salinity gradient" OR "floating photovoltaic") AND ("machine learning" OR "deep learning" OR "computer vision" OR "time series" OR SCADA OR "condition monitoring" OR CFD OR FSI OR "digital twin" OR "physics-informed" OR eDNA OR metabarcoding).

The key evidence base was confined to publications from January 2020 onward to reflect recent developments in sensing, offshore monitoring, and modeling of MRE operations [10,14]. Some older foundational works were included selectively where required to support key concepts.

Table 2. Database-specific search strategies and search settings.

Database	Search Settings	Full Search String (Exact Syntax)
Scopus	Search date(s): 2 December 2025 (updated 7 January 2026) Fields: TITLE-ABS-KEY Filters: January 2020 onward	TITLE-ABS-KEY((biofoul* OR "marine growth" OR biofilm OR barnacle* OR algae OR microfoul* OR macrofoul*) AND ("marine renewable energy" OR "marine energy" OR tidal OR "tidal turbine" OR "wave energy converter" OR OWC OR "offshore wind" OR "floating wind" OR OTEC OR "salinity gradient" OR "floating photovoltaic") AND ("machine learning" OR "deep learning" OR "computer vision" OR "time series" OR SCADA OR "condition monitoring" OR CFD OR FSI OR "digital twin" OR "physics-informed" OR eDNA OR metabarcoding))
Web of Science Core Collection	Search date(s): 2 December 2025 (updated 7 January 2026) Fields: TS Filters: January 2020 onward	TS = ((biofoul* OR "marine growth" OR biofilm OR barnacle* OR algae OR microfoul* OR macrofoul*) AND ("marine renewable energy" OR "marine energy" OR tidal OR "tidal turbine" OR "wave energy converter" OR OWC OR "offshore wind" OR "floating wind" OR OTEC OR "salinity gradient" OR "floating photovoltaic") AND ("machine learning" OR "deep learning" OR "computer vision" OR "time series" OR SCADA OR "condition monitoring" OR CFD OR FSI OR "digital twin" OR "physics-informed" OR eDNA OR metabarcoding))
IEEE Xplore	Search date(s): 2 December 2025 (updated 7 January 2026) Fields: All Metadata Filters: January 2020 onward	("All Metadata":biofoul* OR "All Metadata":"marine growth" OR "All Metadata":biofilm OR "All Metadata":barnacle* OR "All Metadata":algae OR "All Metadata":microfoul* OR "All Metadata":macrofoul*) AND ("All Metadata":"marine renewable energy" OR "All Metadata":"marine energy" OR "All Metadata":tidal OR "All Metadata":"tidal turbine" OR "All Metadata":"wave energy converter" OR "All Metadata":OWC OR "All Metadata":"offshore wind" OR "All Metadata":"floating wind" OR "All Metadata":OTEC OR "All Metadata":"salinity gradient" OR "All Metadata":"floating photovoltaic") AND ("All Metadata":"machine learning" OR "All Metadata":"deep learning" OR "All Metadata":"computer vision" OR "All Metadata":"time series" OR "All Metadata":SCADA OR "All Metadata":"condition monitoring" OR "All Metadata":CFD OR "All Metadata":FSI OR "All Metadata":"digital twin" OR "All Metadata":"physics-informed" OR "All Metadata":eDNA OR "All Metadata":metabarcoding)

1.2.1. Eligibility Criteria

Studies were included if they dealt with biofouling or a clearly defined proxy, e.g., marine growth coverage, roughness increase, biomass accumulation, or community signatures in a MRE device context [15,16]. We shortlisted papers that presented a modeling or decision-support component, hybrid approaches of digital twin, or bioinformatics/eDNA-enabled indicators. We needed enough method reporting to be able to extract source of data or measurement context, modeling approach, and evaluation or validation method [17,18]. We excluded some major works, as they solely focused on coatings/materials that were not connected with modeling results and/or operational effects on MRE. Further, the priority was given to peer-reviewed journal papers and review articles [19,20].

In the screening and selection process, we sent out the records to a reference manager to eliminate duplicates. We screened the data in two phases, a preliminary title/abstract screening in accordance to the eligibility criteria, then finally the full text was evaluated to qualify as a final inclusion [21,22]. Exclusion criteria of the full text were taken. The general workflow is depicted in Figure 1. Two reviewers (S.D. Hasil and Wei Shi) independently screened titles/abstracts and full texts. Disagreements were resolved by discussion; unresolved cases were adjudicated by a third reviewer (Constantine Michailides).

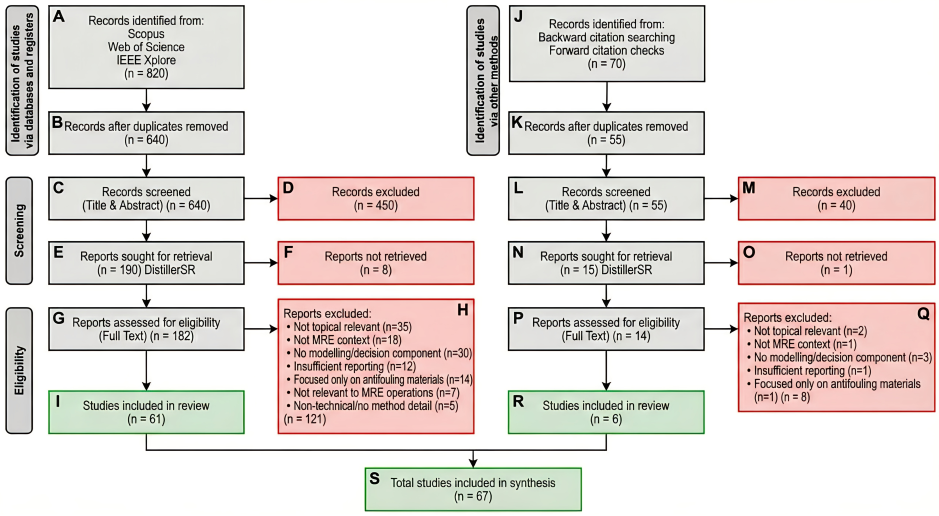

Figure 1. Flow diagram of the literature search and study selection process. Grey boxes indicate identification and screening steps, red boxes indicate excluded or not retrieved records/reports, and green boxes indicate studies included in the review. Records were identified from Scopus, Web of Science Core Collection, and IEEE Xplore (n = 820) and from backward citation searching and forward citation checks (n = 70). After duplicate removal, 640 database records and 55 additional records were screened by title/abstract; 450 and 40 records were excluded at screening, respectively. Full texts were sought for 190 and 15 reports; 8 and 1 reports were not retrieved; 182 and 14 reports were assessed for eligibility. Overall, 67 studies were included in the narrative synthesis (61 from database searches and 6 from other methods).

1.2.2. Study Grouping and Synthesis Framework

Since there is heterogeneity in the classes of the devices, environments, definition of foulings, data modalities, and protocols used in their validation, a structured narrative synthesis was used instead of a meta-analysis [23,24]. Modeling/data modality and engineering decision target were used to group studies. For each of the included studies, we replicated the device and site context, definition of fouling and how it was measured, type of data and sampling, model family, and important design decisions and how they were validated [6,7]. These fields help to cross-study compare the results and the integrated framework presented later on.

2. Biofouling in MRE Devices and Engineering Impacts

2.1. Occurrence and Factors Influencing Biofouling

Biofouling occurs on nearly all submerged components of marine renewable energy (MRE) devices. Colonization typically begins with microbial biofilms and may progress to macrofouling organisms such as mussels, barnacles, algae, and tubeworms over weeks to months [1,25,26]. The composition and growth rate of fouling communities depend on environmental conditions and component location. Key influencing factors include water temperature, nutrient availability, flow velocity, depth, and surface material properties [1,27,28].

Although attachment rates may vary with surface characteristics and hydrodynamic exposure, most offshore structures eventually experience fouling. Importantly, fouling is rarely uniform across a device. Variations in depth, orientation, sunlight exposure, and flow conditions result in spatially heterogeneous growth patterns [1,29]. Figure 2 summarizes the typical hotspot regions observed on tidal turbines, wave energy converters, and offshore wind structures. Hotspot regions are indicative and may vary substantially by site, device geometry, and local conditions; they should not be interpreted as universal. This spatial variability is particularly relevant for modeling and monitoring applications.

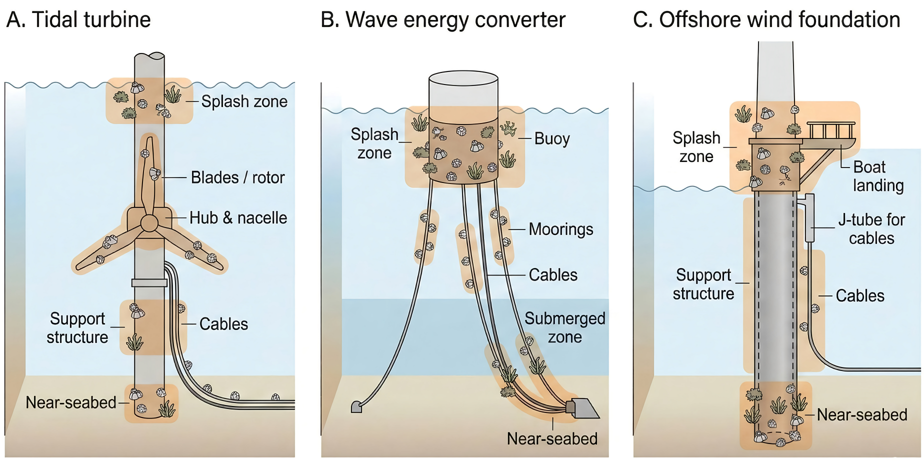

Figure 2. Typical biofouling hotspot regions on marine renewable energy devices (schematic). Common attachment zones (e.g., blades/nacelles, moorings/cables, and monopiles/platform undersides) are shown together with depth/orientation gradients that often drive non-uniform colonization. Hotspot locations are indicative and site-specific, and depend on local conditions (e.g., depth, orientation, sunlight exposure, and flow).

2.2. Engineering Impacts on Performance and Structural Integrity

Biofouling affects MRE performance primarily through increased surface roughness, added mass, and altered hydrodynamic behavior [30,31]. Even relatively thin fouling layers can significantly reduce turbine efficiency. For example, a 1 mm fouling layer on a tidal turbine blade has been reported to reduce lift coefficients by approximately 15% and drastically reduce lift-to-drag ratios [3,32]. Such changes shift performance curves and decrease energy capture.

Accumulated fouling can also increase structural loads and fatigue damage. Added mass and drag amplify thrust forces on blades, nacelles, monopiles, and mooring systems [3,33]. For floating systems, biofouling alters hydrodynamic responses and can affect mooring tensions and natural frequencies [34,35]. Reported studies indicate that heavy fouling can significantly reduce the fatigue life of moorings and structural components [1,36].

Figure 3 conceptually illustrates the cause–effect pathway from fouling growth to hydrodynamic alteration, performance degradation, load amplification, and increased maintenance requirements.

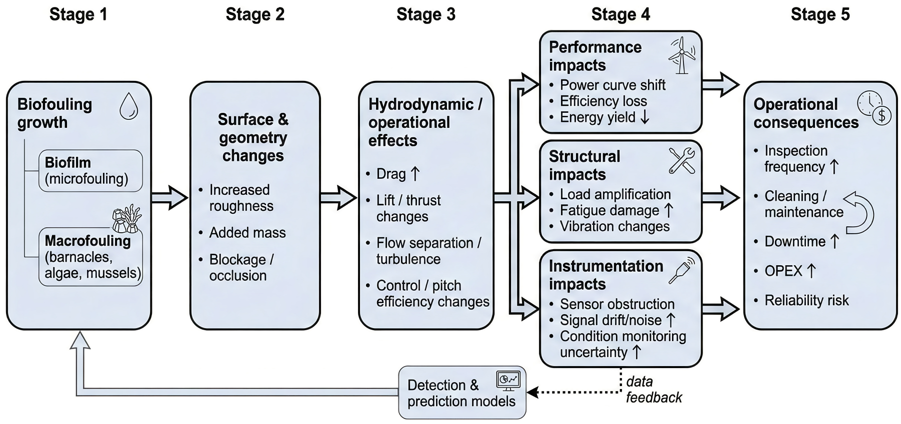

Figure 3. Conceptual cause–effect pathway from biofouling growth to operational and structural impacts. Fouling increases surface roughness and added mass, which can increase drag and alter lift, leading to a power-curve shift (reduced energy capture) and increased loads (e.g., thrust and fatigue). Arrows indicate hypothesized causal links; the pathway is illustrative and not a quantitative model.

2.3. Impacts on Instrumentation and Maintenance

Biofouling also interferes with instrumentation and operational reliability. Sensors, cameras, pressure ports, and flow meters may experience signal distortion or blockage due to biological growth [37,38]. In severe cases, the fouling of cooling systems and power cables can impair heat dissipation and reduce component lifespan [39,40].

These impacts translate into increased maintenance frequency, operational downtime, and higher lifecycle costs [41,42]. Consequently, biofouling management is not only a biological concern but also a performance and asset integrity issue. Effective monitoring and predictive modeling can enable timely cleaning interventions and reduce unplanned outages.

Table 3 summarizes the key biofouling-induced effects and their measurable proxies, highlighting data modalities relevant for modeling and predictive maintenance.

2.4. Thermodynamic Considerations of Biofouling-Induced Energy Losses

While hydrodynamic performance degradation due to biofouling is commonly quantified in terms of increased drag and reduced lift-to-drag ratios, a complementary thermodynamic perspective provides deeper insight into the irreversible energy losses associated with surface roughness and flow disturbance. Marine renewable energy (MRE) systems operate by extracting kinetic energy from moving water and converting it into mechanical and electrical power. Any modification of surface conditions therefore alters the thermodynamic efficiency of this energy conversion process. From a thermodynamic standpoint, biofouling increases viscous dissipation and turbulence intensity in the boundary layer surrounding blades, nacelles, monopiles, and mooring components. Surface roughness elements such as biofilms, barnacles, and calcareous deposits disrupt the viscous sublayer and enhance turbulent mixing, thereby increasing frictional drag and form drag. The mechanics of turbulent flow over rough walls have been extensively studied, demonstrating that surface irregularities significantly amplify momentum transfer and energy dissipation within the boundary layer [43]. This additional drag represents the mechanical energy that is irreversibly converted into internal energy (heat) within the fluid, rather than being captured by the turbine rotor.

Table 3. Data modalities, raw inputs, engineered features, and prediction targets for biofouling modeling in MRE systems.

Modality	**Typical Raw Inputs**	**Engineered Feature Examples**	**Common Targets/Key Limitations**
SCADA/CMS time-series	Power, RPM, torque, pitch, vibration, temperatures	Rolling statistics; spectral bands; change-point features; residuals vs clean baseline	Fouling proxy; power-loss estimate; anomaly class; confounding by controls/metocean; sensor drift; missingness
Metocean context	Wave height/period, current speed, temperature, salinity, turbidity	Context windows/lagged summaries; seasonal indicators; normalization covariates	Growth likelihood; deconfounding covariates; spatial mismatch; gaps; nonstationarity
Inspection images/video	ROV/diver/drone imagery	Segmentation masks; coverage %; texture indices; occlusion/quality score	Coverage class; hotspot detection; thickness proxy; sparse labels; lighting/turbidity shift; cost
Lab + field experiments	Drag/roughness tests; biofilm thickness; coupon measurements	Calibrated parameters; mechanistic priors; fitted coefficients	Calibration targets; controlled benchmarks; lab–field gap; limited representativeness
Bioinformatics (eDNA/biofilm)	OTU/ASV tables; taxa read counts/abundances	Diversity indices; indicator taxa; community-shift metrics; embeddings	Species composition; growth stage; corrosion-risk proxy; sampling frequency limits; sequencing bias; standardization issues

Entropy generation provides a quantitative measure of these irreversibilities. In turbulent flow systems, entropy production is primarily associated with viscous shear stresses and turbulent kinetic energy dissipation [44,45]. The presence of surface roughness increases local velocity gradients and promotes earlier transition to turbulence, thereby increasing entropy generation rates [46]. From a thermodynamic perspective, this corresponds to higher exergy destruction and reduced second-law efficiency of the energy conversion process [47]. Thus, biofouling not only alters hydrodynamic coefficients empirically but also fundamentally changes the thermodynamic pathway through which kinetic energy is transformed into useful work. In tidal turbines and wave energy converters, added mass and roughness-induced damping also modify oscillatory hydrodynamic behavior. Increased damping reduces the fraction of environmental kinetic energy converted into mechanical motion, thereby lowering net useful work output. The resulting decrease in power coefficient can therefore be interpreted as an increase in irreversible losses within the fluid–structure interaction system. This thermodynamic framing complements conventional power-curve analyses and provides a physically grounded explanation of performance degradation.

An exergy-based viewpoint further clarifies the magnitude of efficiency loss. Exergy analysis compares the maximum theoretical work extractable from a flow to the actual work produced [47]. Biofouling increases exergy destruction through enhanced viscous dissipation and turbulence generation, widening the gap between theoretical and realized energy capture. Such thermodynamic descriptors offer physically interpretable indicators that can be integrated into hybrid modeling frameworks. Importantly, recent developments in physics-informed machine learning provide mechanisms for embedding conservation laws and energy balance constraints into predictive models [48,49]. By incorporating thermodynamic reasoning such as entropy generation proxies or efficiency degradation metrics into data-driven algorithms, it becomes possible to improve model interpretability and generalization across varying environmental regimes. This is particularly relevant for offshore deployments, where domain shift may arise from site-specific flow characteristics.

In summary, biofouling-induced degradation can be interpreted as an increase in irreversible energy losses manifested through enhanced viscous dissipation, entropy production, and exergy destruction. A thermodynamic perspective therefore strengthens the physical foundation of performance analysis and supports the development of physics-guided predictive maintenance strategies for marine renewable energy systems.

3. Data and Modeling Methods

3.1. Data Sources

The biofouling of MRE devices must be monitored by collecting a variety of data. One of the main resources is the data given by the operational sensors themselves. In most contemporary turbines and converters of wave energy, the SCADA (Supervisory Control and Data Acquisition) systems record parameters such as power output, rotational speed, torque, blade pitch, electrical current, etc., along with such environmental parameters as tidal current speed, wave height (where possible) [50,51]. Temporal variations of these time-series signals may be an indicator of fouling. As an example, a slow reduction in power coefficient at a constant flow speed, or an increase in drag torque at constant rotation speed, can be an indication of increasing roughness on blades (as shown in carefully controlled experiments) [3,52].

These devices may have condition monitoring systems (CMSs) to provide additional information like vibration spectra or strain gauge measurements or motor current measurements [11]. Changes in vibration or load distributions that could be detected can be caused by fouling. In fact, scientists have proposed the application of generator electrical signals (stator current) in order to identify the development of biofouling in tidal turbines [1,53]. Environmental information is also valuable (so-called metocean information): the temperature of water, its salinity, nutrient content, and seasonal conditions contribute to forecasting the rates of the growth of foulages [54]. Local data or models can give such data.

Also, periodic inspection data play an important role in ground truth. Most of the offshore equipment is surveyed by divers or ROVs that take pictures or videos of the biofouling on the equipment. These images give firsthand observation of the coverage (fouling extent), thickness, and composition (types of organisms). In other instances, quantitative fouling data can be obtained by manual measurements (e.g., scraping a small section of an object and weighing the fouling mass), or by using a coupon/sample capable of being retrieved (e.g., a scraper) [1,55].

Test data in laboratories and in the field can also be used in modeling—e.g., tank or flume experiments in which surfaces are contaminated with known conditions or test sites (such as SEM-REV with floating wind or EMEC with tidal turbines) can provide a correlation between the extent of fouling and performance variation [1]. All these data streams, SCADA/CMS time-series, metocean, and visual inspection and experimental outputs of the inputs to formulate the biofouling modeling of MRE systems, are becoming more dependent on multi-modal inputs. Figure 4 is a summary of the key data streams and the way they lead to modeling (physics-based, ML time-series/regression/vision, and bioinformatics pipelines).

https://doi.org/10.3390/jmse14060549

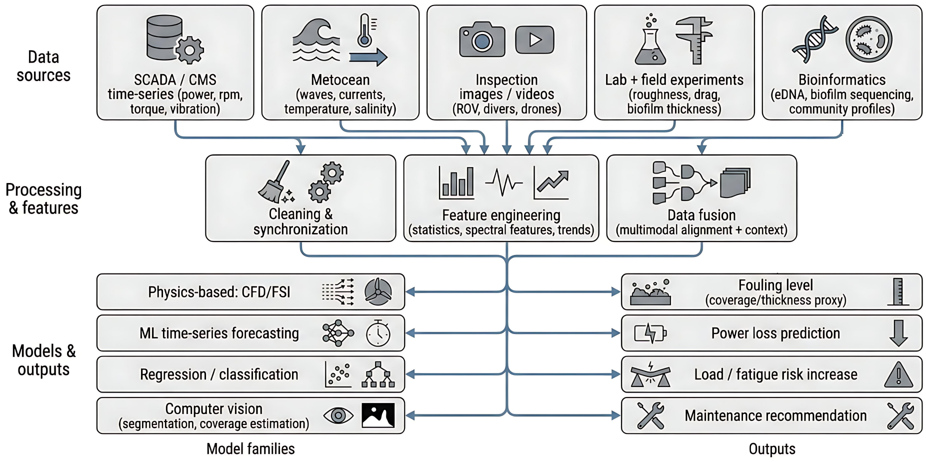

Figure 4. Multi-modal data ecosystem for biofouling modeling in MRE devices (schematic). From left to right, common inputs (SCADA/CMS signals, metocean context, inspection imagery, experimental/field tests, and eDNA/biofilm sequencing outputs) feed feature construction and modeling, including physics-based approaches (CFD/FSI), ML approaches (time-series forecasting, regression/classification, and vision models), and bioinformatics workflows (metabarcoding/community profiling). Typical outputs are fouling state estimates, forecasts, and maintenance-relevant triggers. Abbreviations: SCADA = supervisory control and data acquisition; CMS = condition monitoring system; CFD = computational fluid dynamics; FSI = fluid–structure interaction; eDNA = environmental DNA.

3.2. Numerical and Experimental Modeling

Biofouling effects were traditionally studied, before the rise of machine learning, using physical experiments and numerical simulations. Computational fluid dynamics (CFD) and fluid–structure interaction (FSIs) simulations are applied to measure the effect of added roughness on the performance of the biofouling and mass. As an example, Wright et al. (2022) simulated, using FSI, the floating wind turbine with different fouling thicknesses and roughness and discovered that the influence on platform dynamics and mooring tension is significant [1]. On the same note, tidal turbine CFD models of rough (fouled) turbines have been developed to model power loss and higher thrust as a result of biofouling (this is commonly achieved by introducing a roughness parameter or pseudo barnacle protrusions on blades surfaces) [3].

These are physics-based models that are useful in generating synthetic data and knowledge but need precise knowledge of fouling properties and are computationally expensive. Experimental tests also give useful data: tow-tank or flume tests have been conducted with model turbines or flat plates in which artificial fouling (e.g., roughness strips or object attached) is introduced to measure the effects of drag and lift [1]. Other experiments involve natural fouling, as is the case with immersing samples in the ocean to allow biofouling to occur, and then testing their hydrodynamic characteristics. Spraul et al. (2023) modeled the behavior of mooring lines during fouling by combining field measurements of a test turbine with numerical models [1]. These numerical and experimental techniques are still relevant to justify and guide data-driven models. They are able to give labeled data (e.g., with clean and fouled states) to either train or test multi-layer algorithms.

3.3. Machine Learning Methods

Different machine learning methods within the past years have been pursued to simulate and forecast biofouling-related processes. These are mainly divided into time-series analysis, regression/classification models and computer vision (image-based) models among others. Time-series methods take advantage of the chronological order of the

SCADA or sensor data in order to identify the trends or anomalies caused by fouling. An example is that Laurie et al. (2021) applied ML regression on ship propulsion data in predicting power loss due to hull fouling to show that data-driven models can predict a real-time performance loss due to fouling [56].

Tidal turbines can also be treated similarly: through historical clean performance curves, it is possible to apply algorithms (such as random forests or neural networks) to predict how both the drag and the power change with time due to fouling as a result of the accumulation of foulings. Simple ARIMA models or sequence models (like LSTM neural networks) may predict future growth of fouling or loss in performance based on the past data and seasonal variables. The ML models of regression and classification have been directly applied to predict the levels or categories of fouling. Rashid et al. (2025) proposed an ensemble learning model (RegStack) that took several regression algorithms to forecast tidal turbine power and thrust coefficients under fouling and at the same time estimate the fouling level into clean, light, heavy categories [3].

They stacked their model using regularized linear regressors as a meta-learner and achieved extremely high predictive performance ($R^2 \approx 0.99$) on the measure of performance and 98 percent accuracy in classifying biofouling state [3]. It indicates that, with adequate training data (under a variety of operational and environmental factors) ML models can be used close to predicting the impact of fouling on device functionality. This has also been applied in other works to classify when a turbine is foul and when it is clean using supervised learning based on sensor patterns. As an illustration, a simple classification tree, or support vector machine could be trained on the features such as the drop in power coefficient, the rise in vibration, etc., in order to raise a foul alarm.

Another potent category is computer vision techniques that use marine vegetation images or video on buildings. Convolutional neural network (CNNs) has been used to automatically detect and measure biofouling on the images. Signor et al. (2023) created a deep learning model that identified offshore renewable energy structure images as belonging to one of the fouling categories (mussels, barnacles, Tubeworms, or no fouling) [57]. Their CNN with a limited dataset of approximately 1261 images gave them a general 69 percent detection of the type of macrofouling that was present [57]. Some classes, such as mussels or clean surface, had a higher accuracy (79–81%), and this suggests that with small datasets as well, the vision-based detection will be possible [57]. The authors have observed that it may be possible to enhance the accuracy by increasing the image database and enhancing the model [57].

Rashid et al. (2024) in another study used a real-time object detection model (YOLO v8) to detect biofouling on tidal turbine blades based on the video footage [58]. The system was able to differentiate between fouled and clean blade surfaces when trained on annotated images of turbine blades with fouling based on reports of accuracy of over 97% [58]. The latter type of high-performance detection has promise in automated monitoring cameras on turbines or ROV inspections might be used to feed a model which can assess instantly the coverage of the fouling. Nevertheless, there are difficulties: images underwater may be of low quality, and marine vegetation may be uneven. Rashid et al. (2023) have indicated that difficulties with identifying precise fouling species and thickness based on images only exist particularly in the presence of limited training data [58].

To simplify the vision task, it is possible to concentrate on the estimation of the total foulage coverage or severity rather than on the identification of all the existing species [58]. This has been proposed as being more functional as a method of maintenance decision making; the important thing is that it is known how much fouling (as a percentage or thickness) is on a component, which is correlated to loss of performance, and not the exact taxonomy of the fouling. Such methods as image segmentation or depth estimation can be used to measure the extent of fouling. As an example, there have been studies of algorithms that estimate the thickness of fouling layer using stereo images or structured light, which can be complicated in practice [6]. All these camera angles or video frames across time could enhance reliability because time information can be used to validate growth patterns [6]. In general, image-based ML-based models represent a fast-developing field where the remote inspection of MRE devices can be performed, with a possible, or even absolute, replacement of human surveyors in the workplace. To select a suitable method, Table 4 presents a guide to the selection of models family, the types of tasks to be performed, the requirements of data, strengths and the common failure modes in MRE biofouling applications.

Table 4. Method selection guide for ML and hybrid modeling of biofouling impacts.

Model Family	Best Suited Tasks	Data Need	Strengths	Limitations/Failure Modes	Interp.
Physics-based (CFD/FSI, ROM)	Load/power sensitivity; scenario analysis	Med–High	Mechanistic insight; extrapolation under known physics	Compute cost; needs geometry/BCs; biology hard to encode	High
Statistical baselines (ARIMA/GLM)	Short-horizon forecasting; trend detection	Low	Fast; transparent; strong baselines	Limited nonlinearity; poor under regime shifts	High
Classical ML (RF/XGBoost/SVM)	Tabular regression/classification	Medium	Strong on engineered features; robust on small/medium data	Feature engineering required; temporal structure weaker	Med
Deep time-series (LSTM/TCN)	Sequence forecasting; anomaly detection	High	Learns complex temporal patterns; sensor fusion	Data-hungry; leakage risk; generalization issues	Low
Vision models (U-Net/Mask R-CNN/ViT)	Coverage/thickness estimation; localization	High	Direct fouling quantification; interpretable masks	Label cost; domain shift (lighting/turbidity/view)	Low–Med
Hybrid/physics-informed ML	Constrained prediction; improved robustness	Med–High	Better generalization; uses priors; uncertainty-aware	More complexity; calibration and validation needed	Med

Interp. (interpretability): *High* = model structure/parameters provide direct, stable explanations (e.g., mechanistic/linear baselines); *Med* = partial explanations usable for diagnosis (e.g., feature importance/SHAP and saliency masks); *Low* = largely opaque representations where interpretation is mainly post hoc and may be unstable.

3.4. Bioinformatics and Environmental DNA

Bioinformatics techniques, such as environmental DNA (eDNA) metabarcoding, have recently been used to study the biological side of biofouling. eDNA is DNA that is deposited to the environment by organisms (via excretion, sloughing of cells, etc.) and can be taken from a water sample or scraped from the surface of biofilm. With the high-throughput sequencing of eDNA, it is possible to know the species that are found in a particular location or on a device, without having to physically identify every individual organism [59–61].

For example, Gu et al. (2025) evaluated eDNA metabarcoding for monitoring macrofouling communities in aquaculture net cages and found it effective for detecting diverse fouling taxa [59]. Similarly, Perry et al. (2026) demonstrated that passive eDNA sampling can effectively monitor vessel biofouling in the Southern Ocean [60]. Nam et al. (2025) used comprehensive eDNA metabarcoding to reveal seasonal and antifoulant effects on microbial-metazoan interactions in biofouling communities [61].

These studies show that eDNA can capture both microfouling (bacteria, algae) and macrofouling (invertebrate larvae, adults) signatures. The data from eDNA can be analyzed to calculate diversity indices (e.g., Shannon index and species richness), identify indicator species that correlate with fouling severity, or track shifts in community composition over time. For MRE applications, eDNA could potentially serve as an early warning system: detecting an increase in certain fouling-prone species' DNA in the water before visible fouling accumulates on a device.

Integrating eDNA data with ML models is an emerging frontier. For instance, one could use the relative abundance of key fouling species from eDNA as input features to a model predicting fouling growth rate or coverage in the coming weeks. Bioinformatics pipelines (such as QIIME2 or other metabarcoding tools) process raw sequencing reads into taxonomic tables, which can then be fed into predictive models alongside environmental and operational data. This multi-modal approach (combining biological, environmental, and engineering data) has the potential to improve prediction accuracy and provide insights into the ecological drivers of fouling.

3.5. Machine Learning Integration of eDNA and Bioinformatics Data

While environmental DNA (eDNA) metabarcoding provides a detailed characterization of microbial and macrofouling communities, its practical relevance in marine renewable energy (MRE) applications depends on its transformation into structured features suitable for predictive modeling. In typical workflows, raw sequencing reads undergo quality filtering, trimming, chimera removal, and taxonomic assignment, resulting in operational taxonomic unit (OTU) or amplicon sequence variant (ASV) abundance matrices. These matrices represent relative taxa abundance per sampling instance and form the primary quantitative basis for downstream machine learning (ML) integration. Before model development, abundance tables are generally normalized using compositional transformations such as relative abundance scaling, log-ratio transformation, or rarefaction to account for sequencing depth variability. From these processed data, several biologically meaningful descriptors can be derived, including diversity indices (e.g., Shannon diversity and richness), functional group abundance metrics, dominant taxa proportions, and indicator-species encoding. In high-dimensional datasets, dimensionality reduction techniques such as principal component analysis (PCA) or manifold learning methods may be applied to generate compact embedding representations while preserving community structure. These transformed variables can then be incorporated as structured numerical inputs into predictive models.

Within supervised learning frameworks, eDNA-derived features may be used for both regression and classification tasks relevant to biofouling management. Regression models can estimate fouling thickness, biomass accumulation, drag coefficients, or power-loss percentages based on biological community signatures. Classification models may categorize device condition into operational states such as clean, light fouling, or heavy fouling. When longitudinal sampling is available, eDNA indicators may also be integrated into time-series forecasting models to estimate growth trajectories or seasonal fouling risk. Tree-based ensemble models, support vector machines, and neural network architectures are particularly suited to handling nonlinear relationships between biological abundance patterns and engineering performance variables. A key advantage of eDNA integration lies in its compatibility with multi-modal predictive frameworks. Biological indicators can be fused with operational SCADA residuals, condition-monitoring signals, and metocean covariates to create hybrid models that capture both ecological drivers and engineering responses. In such architectures, eDNA features may be concatenated with sensor-derived variables in classical ML models or incorporated into multi-branch neural networks for joint learning across heterogeneous data streams. This approach enables the earlier detection of fouling-prone conditions before measurable hydrodynamic degradation becomes evident.

Despite its potential, several methodological considerations remain critical, including the high dimensionality of abundance matrices, compositional data constraints, sampling frequency limitations, and site-specific ecological variability. Robust validation strategies particularly time-based splits and cross-site evaluation are necessary to ensure generalization and avoid overfitting. When properly integrated, eDNA-derived descriptors provide a biologically informed extension to engineering-focused predictive maintenance models and support the development of proactive, data-driven biofouling management strategies in MRE systems.

4. Integrated Predictive Framework

One of the aims of the industry is to establish an integrated system that integrates engineering and biological information to forecast the development in biofouling and the effects it has on the performance of the MRE devices, and to make maintenance choices. Such a framework would combine the data sources and models reflected above into a sensible system (often called a digital twin or prognostic health management system) [1,10,14]. The concept is to continually feed the device SCADA data, environmental measurements, inspection images, and perhaps eDNA monitoring results into a single model that provides forecasts of the fouling level, the losses associated with this, and the additional loads as well as the most appropriate time to carry out the maintenance (cleaning or inspections) [3,50,51,58].

In order to realize a combined engineering-bio data system, an architecture is required. Figure 5 shows a reference workflow that takes SCADA/metocean/imagery/eDNA, creates estimates of the fouling state, forecasts performance and load effects, and produces maintenance decisions and feedback to update the model.

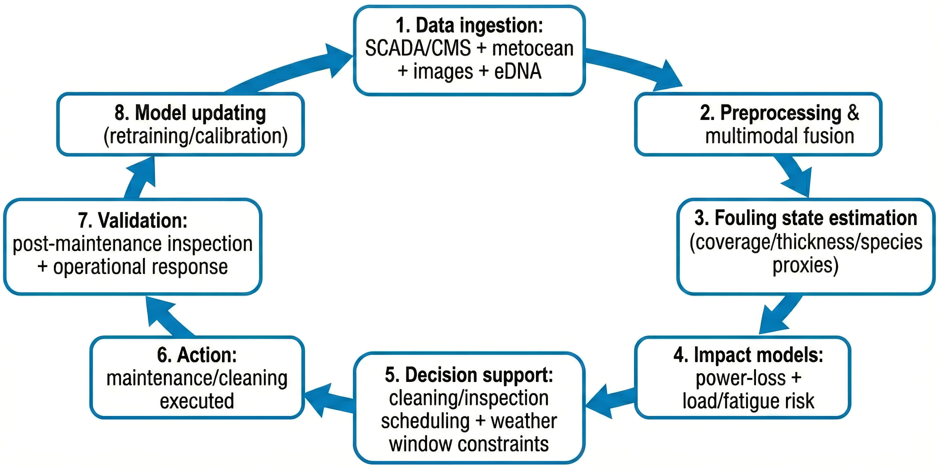

Figure 5. Integrated prediction framework for biofouling-aware performance forecasting and maintenance planning. Reference digital-twin workflow showing (i) data ingestion (SCADA/CMS, metocean, inspection images, and eDNA), (ii) fouling state estimation (coverage/thickness/species proxies), (iii) impact models translating fouling into power-loss and load/fatigue risk, (iv) decision-support outputs (cleaning/inspection timing, weather-window constraints, and uncertainty bounds), and (v) feedback updating through validation against new inspections and operational data.

4.1. Framework Components and Architecture

Fouling growth prediction is one of the constituents in an integrated framework. The framework will be able to predict the rate at which various areas of the device will get covered by foulings by combining metocean data (temperature, nutrients, etc.) with past fouling observations [27,54,62]. In one example, an ML model may get to know that in summer when the sea is calm, biofouling on the blades of a tidal turbine will increase to heavy within X weeks. In the case of the biological data existence such as eDNA showing the presence of some larvae, the model might modify the prediction of the growth rate [59–61]. This is a solution to the occurrence and degree of fouling.

Meanwhile, the framework must also forecast the impairment of performance as a result of the fouling. It can use it to convert a predicted level of fouling into the expected changes in power output and loads using models such as those by Rashid et al. (2025) or others [3,30,31,56]. As an example, when it is forecasted that in two months time the percentage coverage of the blade area will be 50 percent due to fouling, the framework may predict a 10 percent decrease in power coefficient and a 10 percent increase in thrust force.

The predictions can be based on the regressors of past examples which are data driven or on the correlations of physics which has been tested [32,52,63].

4.2. Prediction of Fouling Growth and Performance Impact

More importantly, the framework would offer a decision support tool on maintenance planning. This involves finding out when the fouling is at a point that can be justified into action. Frequent minor quantities of contamination may well be accepted, but beyond a point, the expense becomes excessive (the price of cleaning is lower than the energy loss or the danger of damage it would cause) [41,42,64]. According to [1], when performance is impaired by biofouling, it is imperative to determine when this degradation is serious enough to justify elimination. The combined model is able to predict the date in which the fouling shall reach that threshold assuming nothing is done about it [3,58].

As an example, it can estimate that in month X, the turbine will lose half of its efficiency and mooring fatigue damage is going to increase faster, indicating that it should be cleaned prior to month X [36,65,66]. There are even frameworks which may maximize the schedule based on weather windows and operational schedules, in effect carrying out maintenance planning under uncertainty [10,42]. The product may be a suggested frequency of inspection or a follow-up cleaning date with some confidence.

4.3. Maintenance Decision-Support and Validation

An important caveat is such predictions being checked with the actual field data. Any consolidated framework needs to be tested to verify against real measurements [6,17,18]. This may be in terms of pilot deployment in which the system will predict the level of fouling and so on. Further, performance is compared to follow-up inspection and performance logs. As an example, the model may forecast a 15 percent reduction in power in half a year; once 6 months have elapsed, the model should be amended with the actual SCADA information and photographs to adjust the model [3,50,51].

A case study by Rashid et al. (2025) demonstrated that their ML model was able to be trained to very high accuracy with a large dataset of tidal turbine operations in a variety of fouling conditions [3]. However, in practice, there is no large labeled data on many sites. Therefore, a part of the framework is the ceaseless learning: with the new information (new eDNA results or new performance metrics when some of the data has been cleaned), the model is subsequently updated with new parameters or retrained to yield better predictions in the future [11,53]. Table 5 is a list of the practical maintenance decision metrics and triggers, as well as the anticipated evaluation criteria to show operational value.

4.4. Data Integration and Hybrid Modeling Approaches

A proper data architecture is required in order to combine engineering and bio data. This may imply a database that correlates every timestamp to SCADA readings, environmental parameters and any accessible bioindicator (such as fouling coverage of image, key species concentration of DNA or DNA concentration) [4,5,59–61]. Such methods as data fusion and multi-modal neural networks may be used such that, say, a fouling coverage measure of an image and a time-series of water temperature jointly serve as inputs into a prediction model [8,9,57,58].

It is possible to imagine a hybrid scheme with a mechanistic component that estimates a performance loss due to foulings coverage (physics relation-based estimation) and a ML component that estimates foulings coverage due to environmental and biological indicators [30–32,67]. This type of hybrid model is capable of exploiting domain knowledge and at the same time being data driven [1]. In fact, it has been proposed that physical knowledge can be added to ML models (e.g., by defining custom loss functions that can guarantee physical consistency) to better predict fouling and other marine growth problems [1,53]. This minimizes the use of only black box models and is able to address scenarios outside the training data.

Table 5. Maintenance decision metrics and example trigger criteria for biofouling management in MRE systems.

Decision Metric	Example Trigger Criteria (Illustrative)	Basis	Notes/Evaluation
Power loss/power-curve deviation	e.g., >10% drop from clean baseline (metocean-corrected), sustained ≥7–14 d	Calibrate	Validate with post-cleaning recovery; check sensitivity to season/control settings [41,42,64].
Image-derived fouling coverage	e.g., >50% coverage of critical surfaces, or growth >10% over 2–4 w	Calibrate	Tie coverage to performance/loads for the device; report segmentation accuracy and domain shift [1,55].
Load/fatigue proxy (thrust, tension)	e.g., >15% increase vs clean baseline under matched regime	Literature + calibrate	Validate with load sensors/strain; compare distributions across matched metocean windows [36,65,66].
Sensor/data-quality gate	e.g., drift >5%, persistent bias, or sustained dropout beyond limits	Practice-based	Treat as a gate (sensor fouling can mimic device fouling); cross-check redundant sensors [11,53].
eDNA settlement-risk indicator	e.g., marker concentration > baseline by 3× for ≥2 consecutive samples	Literature + calibrate	Check lagged association with observed settlement/coverage; require controls and pipeline consistency [59–61].
Economic decision rule	Clean now if $C_{clean} < C_{loss} + C_{risk}$ over horizon	Practice-based	Report assumed costs/downtime; do sensitivity analysis [10,41,42,64].
Weather-window feasibility	Suitable access window within next 30 d (or operational horizon)	Practice-based	Use as constraint on scheduling; compare planned vs achieved dates [10].

Notes. "Basis" indicates whether the trigger is mainly illustrative (requires site calibration), practice-based (common O&M logic), or supported by prior literature examples but still requiring calibration. "Clean baseline" should be defined using a verified low-fouling period (e.g., post-cleaning) under comparable operating conditions, with metocean correction where possible. For the *eDNA baseline trigger*, baseline can be defined as the median (or geometric mean) marker concentration over a rolling window during a confirmed low-fouling period at the same site, processed with the same marker and bioinformatics pipeline and including negative/positive controls; a practical trigger is exceedance by the chosen factor in at least two consecutive sampling events [59–61].

4.5. Digital Twin Implementation and Proactive Management

The concept of digital twin technology is very applicable in this case. A digital twin is a digital replica of the physical object tracking the real-time condition of the object with the assistance of sensor inputs and simulations [10,14,42]. In a case where an offshore energy device is involved, biofouling may be incorporated within a digital twin simulation model that models the fouling growth and its dynamics. The recent literature emphasizes the possibility of sensor-based digital twins to improve the maintenance of offshore systems that can be implemented to tidal turbines and other MRE to manage fouling [1,10].

Operators can execute what-if scenarios by updating the twin on the existing fouling extent (measured through images or estimated through performance data). As an illustration, the twin might model the behavior of the turbine during a storm with the existing fouling, or how it would actually behave with a cleaning today as compared to 2 months later [34,35,68]. This assists in the decision-making of maintenance that is risk-cost balanced. The combined framework may therefore incorporate a simulative element with pure ML elements.

Finally, a unified prediction system should be used to ensure that biofouling management is no longer reactive but proactive. Rather than waiting until power drops or equipment fails because of fouling, operators would anticipate future fouling levels and performance and they would schedule the cleaning or inspection in the most optimal way [41,42,64]. An effective framework may, as an example, signal to alert that the biofouling of turbine 3 is likely to result in a 8% power loss and to approach the safe load limit of the moorings by December and therefore needs maintenance in November.

The first applications of such predictive maintenance of fouling are in research. One example is the compilation of a biofouling database in a European project to aid in the prediction of the species and degree of fouling to occur at a particular site to allow specific planning of a site [33,55]. Rashid et al. (2023) developed a roadmap that combines detection and prognostics, highlighting the fact that the calculation of the remaining useful life prior to the removal of foulants is one of the objectives [58].

The integrated framework is yet to be a mature idea, and there are still issues in making it robust (discussed next). Nevertheless, the components of it, including data pipelines, ML/physics models, and validation methods, are slowly coming together. Early case studies demonstrate that engineering and bioinformatics information can enhance the accuracy of the prediction of fouling in comparison with either one individually [3–5,59]. These frameworks will become increasingly possible and effective as sensing technology becomes more affordable (e.g., lower-cost underwater cameras and automated eDNA samplers) and more data is shared across projects [37,38,69]. The following section presents the primary problems we have encountered in creating and implementing such predictive models and proposes paths that a future study would take to overcome the existing drawbacks.

5. Challenges and Future Directions

Developing comprehensive ML and bioinformatics solutions for biofouling in MRE systems comes with several challenges.

5.1. Data Scarcity and Quality Limitations

Data quality and availability is one of the main problems. There are very few high-quality datasets that correlate the level of fouling with the performance of the device in the open market [1]. Most of the studies that have been done so far are based on small sample sizes (a few months of data or a few hundred images), which limits model training and validation. Shared or benchmark databases of biofouling in MRE do not exist. The whole process of a project usually gathers its own data, under certain conditions, and it is difficult to extrapolate models.

The way forward should be towards future endeavors preparing open databases of fouling observations (images, sensor data, eDNA samples) at various sites and device types. The database on European biofouling by Vinagre et al. (2020) is one such move, yet it gathers data on species presence, fouling thickness and weight of various areas [55]. The growth of such databases and promotion of data sharing (possibly via international activities or the OpenMODs to marine energy) would significantly contribute to the creation of generalized and strong models.

5.2. Model Generalization and Transferability

There is also the issue of generalization and transferability of models. The phenomenon of biofouling is very local because the species profile and growth rate varies according to region and even amongst adjacent locations. An ML model that was trained on data of one tidal turbine (with some species of fouling prevalent there) might prove to be not effective on another turbine elsewhere. In areas where the fouling community is not the same as in the training data, one challenging situation is the deployment of a model [58].

In these situations, the model will be misclassified or miss prediction, since it will be facing new patterns (e.g., another dominant fouler). To overcome this, researchers propose either local data fine-tuning models or creating models that address generic indicators (such as total coverage) instead of showing specific species [58]. Few-shot learning or transfer learning methods would enable a base model to be adapted to new sites with limited new data. Also, uncontrollable learning may recognize general characteristics of fouling development that are generalized. In the future, it will be relevant to develop the models that will be flexible and include expertise knowledge on local fouling. In order to achieve reliability, validation under a range of conditions should be performed (tropical waters vs cold waters, and high-flow vs low-flow sites).

5.3. Uncertainty Quantification and Extreme Conditions

The other area that needs to be addressed is uncertainty quantification. The nature of predictions of fouling and its consequences will always be uncertain because of natural variability (e.g., such unpredictable events as mass spawning or storm may change the fouling dynamics). Models should provide not only point estimates but also confidence limits. This is essential to allowing operators to take informed risky decisions (i.e., there is a 90 per cent probability that fouling will be an avoidable amount in two months more, vs. 50 per cent probability).

Uncertainty can be estimated using methods such as probabilistic modeling, Bayesian neural networks or ensemble predictions. Extreme conditions are an especial problem of interest—how will the model extrapolate to the conditions that it has not observed (a marine heatwave leading to an abnormal fouling bloom, or an extreme storm that could sweep away some fouling)? There will be a need to test the models of stress testing on such scenarios, and this may involve the use of extremes of physics.

5.4. Domain Shift, Generalization, and Transfer Learning in MRE Biofouling Models

A critical challenge in deploying machine learning (ML) models for biofouling prediction in marine renewable energy (MRE) systems is domain shift, i.e., the mismatch between the statistical properties of training data and those encountered during real-world operation at different sites or under varying environmental conditions. Offshore environments exhibit substantial variability in temperature, salinity, turbidity, flow regimes, nutrient availability, and species composition. In addition, device geometry, material coatings, sensor calibration, and maintenance histories differ across installations. These factors can significantly alter the joint distribution of input features and prediction targets, thereby degrading model performance when transferred across locations. In the context of biofouling modeling, domain shift may arise in multiple forms. Covariate shift occurs when environmental variables or biological abundance profiles differ between sites, even if the underlying fouling mechanisms are similar. Label shift may emerge when the distribution of fouling severity classes varies seasonally or geographically. More complex distributional changes can occur when ecological communities differ fundamentally across climatic regions, leading to distinct growth dynamics and hydrodynamic responses. As a result, models trained on data from one offshore wind farm or tidal deployment may fail to generalize reliably to another without adaptation.

Addressing these challenges requires explicit consideration of transfer learning and domain adaptation strategies. Transfer learning enables knowledge acquired from one domain to be leveraged in another, reducing the need for extensive labeled data in newly deployed systems. For example, pretrained neural networks for image-based fouling detection may be fine-tuned using limited site-specific inspection data. Similarly, regression models trained on historical SCADA and metocean datasets from one installation can be adapted to new sites through parameter recalibration or representation learning techniques. In cases where labeled data are scarce, few-shot learning or meta-learning approaches may improve adaptability by emphasizing invariant structural relationships rather than site-specific patterns. Domain adaptation methods further support cross-site robustness by aligning feature distributions between source and target domains. Techniques such as feature normalization, adversarial domain alignment, and invariant risk minimization aim to extract representations that are less sensitive to environmental variability. In hybrid modeling contexts, embedding physics-based constraints such as hydrodynamic scaling laws or thermodynamic efficiency limits can also reduce overfitting to site-specific artifacts and enhance extrapolation capability.

For bioinformatics-driven models, domain shift may be particularly pronounced due to ecological heterogeneity. Microbial and macrofouling communities differ significantly across geographic regions, and sequencing pipelines may introduce additional batch effects. Standardization protocols, cross-site validation, and embedding-based dimensionality reduction can mitigate these effects, but robust generalization remains an open research question. Future research should therefore prioritize multi-site benchmarking datasets and systematic cross-validation frameworks that explicitly test model transferability. Ultimately, the long-term viability of data-driven biofouling management in MRE systems depends not only on predictive accuracy within a single deployment but also on robustness across diverse environmental and operational conditions. Integrating transfer learning, domain adaptation, and physics-informed constraints represents a promising pathway toward scalable and deployable predictive maintenance solutions in offshore renewable energy infrastructure.

5.5. Multidisciplinary Data Integration and Standardization

The other issue is the problem of coordinating multidisciplinary data streams. It is not easy to combine physical sensor data and biological eDNA data. These data are of vastly different time scales and format. Interdisciplinary knowledge is needed to put them into correspondence with each other and to explain one by the other. The interaction mechanisms involved between environment, biology and fouling results are yet to be clear as observed in a recent review [2].

Further studies should be done to explain the quantitative effect of microfouling and environmental parameters on macrofouling development on equipment. Such knowledge can be used to inform feature engineering of ML models (e.g., make composite indices of foulings pressure out of many variables). On top of that, it will assist in the standardization of measurements and reporting of fouling. Now one of the studies may be based on percentage cover, another on mass per area, another on a subjective rating. The development of standard measures or interconnection would help with the development of models and comparison.

5.6. Computational, Deployment, and Future Directions

Computational and deployment problems must also be mentioned. It is computationally expensive to train complex deep learning models on large datasets (images or sequence data). ML models could also need to be deployed to the edge or on-site, which may need edge computing hardware that can be deployed to an FPGA or a small computer on a turbine to perform real-time monitoring. The issue of reliability is also a concern in the rugged marine environment; any sensors or cameras used to feed the model must endure biofouling on their own or they need to be self-cleaning.

The data strategy would be complemented by innovative sensor designs (such as antifouling coatings on camera lenses, or flush-mounted vibration sensors that are less likely to foul) and novel sensor designs. The monitoring system itself is also a challenge to maintain: the system should preferably know when its own sensors are contaminated and correct or warn of cleaning.

Looking forward, several future directions emerge.

Physics-informed and hybrid models: First and foremost, the combination of first-principles physics with existing data-driven ML can enhance prediction in the cases not covered by the training data. As an illustration, one can add to the structure of an ML algorithm a roughness-based drag model that will make the algorithm behave reasonably in high-fouling situations. Recent views (e.g., Benbouzid and colleagues, 2023) propose the insertion of loss terms or constraints on ML models based on the physics of prognostics [1]. This will help to address problems of non-consistent labeling and give physical interpretability to the predictions.

Development of digital twins: According to the commentary, digital twins of MRE devices, which have fouling modules, are promising [1]. New applications could be shown in the future and prove that digital twins can effectively predict the dynamics of fouling, as well as optimizing maintenance intervals. This may include cooperation between designers (including physics models of the device), marine biologists (including ecological modeling of fouling) and data scientists (including encasing it in an ML- assisted platform). The pioneers could be flown on one turbine or platform to measure the gains (e.g., an amount of energy was used because the twin implied an ideal cleaning time).

Benchmark datasets and competitions: To encourage innovation, the community might come up with benchmark challenges, such as a dataset of known fouling events on turbines and ask teams to create algorithms to recognize/predict fouling. Other areas (such as wind turbine fault prediction) have demonstrated that a parallel can be used to improve progress faster. As MRE is a smaller field; international cooperation (via IEA-OES projects or EU projects) may be able to collect and contribute sufficient data towards this.

Improved bioinformatics integration: eDNA and bioinformatics integration are in their early stages of adoption. Future research can look into real-time or near-real-time eDNA monitoring (e.g., autonomous DNA samplers that periodically transmit data) and the way to input that into predictive models. It may be possible to use simpler indices by the identification of specific biofouling indicative species by DNA that correlate strongly with operational impacts.

6. Conclusions

This review summarizes the recent work on using machine learning and bioinformatics to study and manage biofouling in marine renewable energy (MRE) devices, including offshore wind, tidal turbines, and wave energy converters. It brings together where fouling tends to occur on devices, what it changes in performance and loads, what data and models are used to predict it, and what is needed to turn predictions into maintenance actions. Biofouling increases surface roughness and added mass, raises drag and viscous dissipation, and can reduce energy capture, increase structural loads, degrade sensors, and increase maintenance costs. Recent studies increasingly use SCADA/CMS time-series, metocean variables, inspection imagery, and laboratory or field measurements to estimate fouling state and to predict performance loss, using approaches that range from classical regression and anomaly detection to deep learning and computer vision. Physics-based models (e.g., CFD/FSI) and thermodynamic viewpoints (e.g., irreversible loss and efficiency degradation) help explain why fouling reduces performance and can also support more interpretable, physics-guided hybrid models. Bioinformatics tools, especially eDNA metabarcoding, add a new way to monitor community change and settlement risk and may provide earlier warnings, but this area is still early-stage and needs consistent sampling protocols, clear baseline definitions, and stronger links to operational targets before it can be used reliably for maintenance decisions. Integrated frameworks such as fouling-aware digital twins are promising, but most evidence remains site specific and is limited by scarce labeled data, inconsistent fouling metrics, limited cross-site validation, and weak uncertainty reporting. Future progress will benefit from standardized measurements and reporting, shared benchmark datasets, stronger validation across independent sites and seasons, and decision-focused evaluations that link model outputs to inspection timing, cleaning triggers, access constraints, and cost–risk trade-offs. These steps can support more proactive and cost-effective biofouling management as MRE deployment expands.

Author Contributions: Conceptualization, S.D.H. and C.M.; methodology, S.D.H. and Z.Z.; formal analysis, S.D.H. and Z.Z.; investigation, S.D.H. and Z.Z.; resources, W.S. and F.I.; data curation, S.D.H.; writing—original draft preparation, S.D.H., Z.Z. and F.I.; writing—review and editing, all authors; visualization, S.D.H. and Z.Z.; supervision, C.M. and W.S.; project administration, C.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors thank the reviewers for their constructive feedback.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Poozesh, P.; Nieto, F.; Fernández, P.M.; Ríos, R.; Díaz-Casás, V. Biofouling on offshore wind energy structures: Characterization, impacts, mitigation strategies, and future trends. *J. Mar. Sci. Eng.* **2025**, *13*, 1363. [CrossRef]
2. Wang, J.; Li, X.; Zheng, L.; Li, Y. Biofouling prevention and control technology for marine engineering equipment: From traditional methods to intelligent interface engineering. *Mar. Pollut. Bull.* **2026**, *223*, 118924. [CrossRef] [PubMed]
3. Rashid, H.; Hanzla, M.; Berghout, T.; Amirat, Y.; Banerjee, A.; Mamoune, A.; Benbouzid, M. RegStack machine learning model for accurate prediction of tidal stream turbine performance and biofouling. *Expert Syst. Appl.* **2025**, *283*, 127766. [CrossRef]
4. Cordier, T.; Forster, D.; Dufresne, Y.; Martins, C.I.M.; Stoeck, T.; Pawlowski, J. Supervised machine learning outperforms taxonomy-based environmental DNA metabarcoding applied to biomonitoring. *Mol. Ecol. Resour.* **2018**, *18*, 1381–1391. [CrossRef] [PubMed]
5. Frühe, L.; Cordier, T.; Dully, V.; Breiner, H.W.; Lentendu, G.; Pawlowski, J.; Martins, C.; Wilding, T.A.; Stoeck, T. Supervised machine learning is superior to indicator value inference in monitoring the environmental impacts of salmon aquaculture using eDNA metabarcodes. *Mol. Ecol.* **2021**, *30*, 2988–3006. [CrossRef] [PubMed]
6. Yebra, D.; Kiil, S.; Dam-Johansen, K. Antifouling technology—past, present and future steps towards efficient and environmentally friendly antifouling coatings. *Prog. Org. Coat.* **2004**, *50*, 75–104. [CrossRef]
7. Chambers, L.; Stokes, K.; Walsh, F.; Wood, R. Modern approaches to marine antifouling coatings. *Surf. Coat. Technol.* **2006**, *201*, 3642–3652. [CrossRef]
8. García Márquez, F.; Tobias, A.; Pinar Pérez, J.; Papaelias, M. Condition monitoring of wind turbines: Techniques and methods. *Renew. Energy* **2012**, *46*, 169–178. [CrossRef]
9. Tchakoua, P.; Wamkeue, R.; Ouhrouche, M.; Slaoui-Hasnaoui, F.; Tameghe, T.; Ekemb, G. Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies* **2014**, *7*, 2595–2630. [CrossRef]
10. Rinaldi, G.; Thies, P.; Johanning, L. Current status and future trends in the operation and maintenance of offshore wind turbines: A review. *Energies* **2021**, *14*, 2484. [CrossRef]
11. Yang, W.; Tavner, P.; Crabtree, C.; Feng, Y.; Qiu, Y. Wind turbine condition monitoring: Technical and commercial challenges. *Wind Energy* **2014**, *17*, 673–693. [CrossRef]
12. Liberati, A.; Altman, D.; Tetzlaff, J.; Mulrow, C.; Gøtzsche, P.; Ioannidis, J.; Clarke, M.; Devereaux, P.; Kleijnen, J.; Moher, D. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *PLoS Med.* **2009**, *6*, e1000100. [CrossRef]

13. Page, M.; McKenzie, J.; Bossuyt, P.; Boutron, I.; Hoffmann, T.; Mulrow, C.; Shamseer, L.; Tetzlaff, J.; Akl, E.; Brennan, S. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
14. Carroll, J.; McDonald, A.; McMillan, D. Reliability comparison of wind turbines with DFIG and PMG drive trains. *IEEE Trans. Energy Convers.* **2015**, *30*, 663–670. [CrossRef]
15. Schultz, M.; Bendick, J.; Holm, E.; Hertel, W. Economic impact of biofouling on a naval surface ship. *Biofouling* **2011**, *27*, 87–98. [CrossRef]
16. Manov, D.; Chang, G.; Dickey, T. Methods for reducing biofouling of moored optical sensors. *J. Atmos. Ocean. Technol.* **2004**, *21*, 958–968. [CrossRef]
17. Delauney, L.; Compère, C.; Lehaitre, M. Biofouling protection for marine environmental sensors. *Ocean Sci.* **2010**, *6*, 503–511. [CrossRef]
18. Callow, M.; Callow, J. Marine biofouling: A sticky problem. *Biologist* **2002**, *49*, 10–14.
19. Flemming, H.; Wingender, J. The biofilm matrix. *Nat. Rev. Microbiol.* **2010**, *8*, 623–633. [CrossRef] [PubMed]
20. Dürr, S.; Watson, D. Biofouling and antifouling in aquaculture. *Biofouling* **2010**, *12*, 267–287.
21. Mieszkin, S.; Callow, M.; Callow, J. Interactions between microbial biofilms and marine fouling algae: A mini review. *Biofouling* **2013**, *29*, 1097–1113. [CrossRef] [PubMed]
22. Qian, P.; Lau, S.; Dahms, H.; Dobretsov, S.; Harder, T. Marine biofilms as mediators of colonization by marine macroorganisms: Implications for antifouling and aquaculture. *Mar. Biotechnol.* **2007**, *9*, 399–410. [CrossRef]
23. Wahl, M. Marine epibiosis. I. Fouling and antifouling: Some basic aspects. *Mar. Ecol. Prog. Ser.* **1989**, *58*, 175–189. [CrossRef]
24. Railkin, A. *Marine Biofouling: Colonization Processes and Defenses*; CRC Press: Boca Raton, FL, USA, 2004.
25. Dobretsov, S.; Thomason, J. The development of marine biofilms on two commercial non-biocidal coatings: A comparison between silicone and fluoropolymer technologies. *Biofouling* **2011**, *27*, 869–880. [CrossRef]
26. Holm, E.; Schultz, M.; Haslbeck, E.; Talbott, W.; Field, A. Evaluation of hydrodynamic drag on experimental fouling-release surfaces, using rotating disks. *Biofouling* **2004**, *20*, 219–226. [CrossRef]
27. Swain, G.; Schultz, M. The testing and evaluation of non-toxic antifouling coatings. *Biofouling* **1996**, *10*, 187–197. [CrossRef]
28. Scardino, A.; Fletcher, L.; Lewis, J. Fouling control using air bubble curtains: Protection for stationary vessels. *J. Mar. Eng. Technol.* **2009**, *8*, 3–10. [CrossRef]
29. Bannister, J.; Sievers, M.; Bush, F.; Bloecher, N. Biofouling in marine aquaculture: A review of recent research and developments. *Biofouling* **2019**, *35*, 631–648. [CrossRef]
30. Strom-Tejsen, J.; Yeh, H.; Moran, D. Added resistance due to roughness of hull surface. *Trans. Soc. Nav. Archit. Mar. Eng.* **1976**, *84*, 197–217.
31. Haslbeck, E.; Bohlander, G. Microbial biofilm effects on drag—Lab and field. *Nav. Eng. J.* **1992**, *104*, 64–72.
32. Walker, J.; Schultz, M.; Flack, K.; Lust, E. The effect of a barnacle-type fouling on tidal turbine performance. In Proceedings of the 4th International Conference on Ocean Energy (ICOE 2012), Dublin, Ireland, 17–19 October 2012; pp. 1–6.
33. Loxton, J.; Macleod, A.; Nall, C.; McCollin, T.; Machado, I.; Simas, T.; Vance, T.; Kenny, C.; Want, A.; Miller, R. Setting an agenda for biofouling research for the marine renewable energy industry. *Int. J. Mar. Energy* **2017**, *19*, 292–303. [CrossRef]
34. Ma, K.; Luo, Y.; Kwan, T.; Wu, Y. *Mooring System Engineering for Offshore Structures*; Gulf Professional Publishing: Houston, TX, USA, 2019.
35. Fontaine, E.; Langlois, S.; Langre, E.; Liao, H. Vortex-induced vibrations of a long flexible cylinder in shear flow. *J. Fluids Struct.* **2006**, *22*, 719–730.
36. Sethuraman, L.; Venugopal, V. Hydrodynamic response of a stepped-spar floating wind turbine: Numerical modelling and tank testing. *Renew. Energy* **2013**, *52*, 160–174. [CrossRef]
37. Whelan, J.; Stallard, T. Arguments for modifying the geometry of a scale model rotor. In Proceedings of the 9th European Wave and Tidal Energy Conference (EWTEC 2011), Southampton, UK, 5–9 September 2011; pp. 1–8.
38. Bahaj, A.; Molland, A.; Chaplin, J.; Batten, W. Power and thrust measurements of marine current turbines under various hydrodynamic flow conditions in a cavitation tunnel and a towing tank. *Renew. Energy* **2007**, *32*, 407–426. [CrossRef]
39. Salta, M.; Wharton, J.; Blache, Y.; Stokes, K.; Briand, J. Marine biofilms on artificial surfaces: Structure and dynamics. *Environ. Microbiol.* **2013**, *15*, 2879–2893. [CrossRef] [PubMed]
40. Marty, A.; Schoefs, F.; Soulard, T.; Berhault, C.; Facq, J. Effect of marine growth on offshore wind turbines: Monitoring and modelling. *J. Phys. Conf. Ser.* **2020**, *1669*, 012023.
41. Hopkins, G.; Forrest, B.; Jiang, W.; Gardner, J. Successful eradication of a non-indigenous marine bivalve from a subtidal soft-sediment environment. *J. Appl. Ecol.* **2011**, *48*, 424–431. [CrossRef]
42. Rinaldi, G.; Thies, P.; Walker, R.; Johanning, L. On the analysis of a wave energy farm with focus on maintenance operations. *J. Mar. Sci. Eng.* **2016**, *4*, 51. [CrossRef]
43. Jiménez, J. Turbulent Flows over Rough Walls. *Annu. Rev. Fluid Mech.* **2004**, *36*, 173–196. [CrossRef]

44. Bejan, A. Entropy Generation Minimization: The New Thermodynamics of Finite-Size Devices and Finite-Time Processes. *J. Appl. Phys.* **1996**, *79*, 1191–1218. [CrossRef]
45. Herwig, H.; Kock, F. Direct and Indirect Methods of Calculating Entropy Generation Rates in Turbulent Convective Heat Transfer Problems. *Heat Mass Transf.* **2007**, *43*, 207–215. [CrossRef]
46. Kock, F.; Herwig, H. Local Entropy Production in Turbulent Shear Flows: A High-Reynolds Number Model with Wall Functions. *Int. J. Heat Mass Transf.* **2004**, *47*, 2205–2215. [CrossRef]
47. Dincer, I.; Rosen, M.A. *Exergy: Energy, Environment and Sustainable Development*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 2013.
48. Raissi, M.; Perdikaris, P.; Karniadakis, G.E. Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations. *J. Comput. Phys.* **2019**, *378*, 686–707. [CrossRef]
49. Brunton, S.L.; Noack, B.R.; Koumoutsakos, P. Machine Learning for Fluid Mechanics. *Annu. Rev. Fluid Mech.* **2020**, *52*, 477–508. [CrossRef]
50. Schubel, P.; Crossley, R.; Boateng, E.; Hutchinson, J. Review of structural health and cure monitoring techniques for large wind turbine blades. *Renew. Energy* **2013**, *51*, 113–123. [CrossRef]
51. Hameed, Z.; Hong, Y.; Cho, Y.; Ahn, S.; Song, C. Condition monitoring and fault detection of wind turbines and related algorithms: A review. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1–39. [CrossRef]
52. Frost, C.; Evans, P.; Harrold, M.; Mason, J.; Chesher, A. The performance of marine current energy conversion devices in the presence of regular waves and turbulence. *Proc. Inst. Mech. Eng. Part M* **2015**, *229*, 133–149.
53. Benbouzid, M.; Berghout, T.; Sarma, N.; Djurović, S.; Wu, Y.; Ma, X. Intelligent condition monitoring of wind power systems: State of the art review. *Energies* **2021**, *14*, 5967. [CrossRef]
54. Neill, S.; Hashemi, M. *Fundamentals of Ocean Renewable Energy: Generating Electricity from the Sea*; Academic Press: Cambridge, MA, USA, 2018.
55. Vinagre, P.; Simas, T.; Cruz, E.; Pinori, E.; Svenson, J. Marine Biofouling: A European Database for the Marine Renewable Energy Sector. *J. Mar. Sci. Eng.* **2020**, *8*, 495. [CrossRef]
56. Laurie, A.; Anderlini, E.; Dietz, J.; Thomas, G. Machine learning for shaft power prediction and analysis of fouling related performance deterioration. *Ocean Eng.* **2021**, *234*, 108886. [CrossRef]
57. Signor, J.; Schoefs, F.; Quillien, N.; Damblans, G. Automatic classification of biofouling images from offshore renewable energy structures using deep learning. *Ocean Eng.* **2023**, *288*, 115928. [CrossRef]
58. Rashid, H.; Habbouche, H.; Amirat, Y.; Mamoune, A.; Titah-Benbouzid, H.; Benbouzid, M. B-FLOWS: Biofouling Focused Learning and Observation for Wide-Area Surveillance in Tidal Stream Turbines. *J. Mar. Sci. Eng.* **2024**, *12*, 1828. [CrossRef]
59. Gu, Y.; Wang, J.; Dong, Y. Evaluating the Use of eDNA Metabarcoding for Monitoring Macrofouling Communities in Net Cage Aquaculture. *J. Ocean Univ. China* **2025**, *24*, 1401–1413. [CrossRef]
60. Perry, F.; Shaw, J.; Cassey, P.; Coutts, A.; Lewis, P.; MacDonald, A.; Polanowski, A.; Stark, J.; Suter, L. Passive environmental DNA (eDNA) sampling is effective for monitoring vessel biofouling in the Southern Ocean. *Sci. Total Environ.* **2026**, *1013*, 181230. [CrossRef]
61. Nam, S.; Kim, S.; Jang, M.; Jung, J.; Shin, K.; Rhee, J. Seasonal and antifoulant effects on microbial–metazoan interactions in biofouling communities revealed by comprehensive eDNA metabarcoding. *Mar. Pollut. Bull.* **2025**, *222*, 118884. [CrossRef]
62. Molino, P.; Wetherbee, R. The biology of biofouling diatoms and their role in the development of microbial slimes. *Biofouling* **2008**, *24*, 365–379. [CrossRef]
63. Schultz, M. Effects of coating roughness and biofouling on ship resistance and powering. *Biofouling* **2007**, *23*, 331–341. [CrossRef] [PubMed]
64. Demirel, Y.; Turan, O.; Incecik, A. Predicting the effect of biofouling on ship resistance using CFD. *Appl. Ocean Res.* **2017**, *62*, 100–118. [CrossRef]
65. Wright, C.; Pakrashi, V.; Murphy, J. The dynamic effects of marine growth on a tension moored floating wind turbine. *J. Phys. Conf. Ser.* **2022**, *2362*, 012023.
66. Wolfram, J.; Theophanatos, A. The effects of marine fouling on the fluid loading of cylinders: Some experimental results. *Proc. Inst. Civ. Eng.* **1985**, *79*, 517–527.
67. Walker, J.; Flack, K.; Lust, E.; Schultz, M.; Luznik, L. Experimental and numerical studies of blade roughness and fouling on marine current turbine performance. *Renew. Energy* **2014**, *66*, 257–267. [CrossRef]
68. Marty, A.; Schoefs, F.; Damblans, G.; Facq, J.V.; Gaurier, B.; Germain, G. Experimental study of two kinds of hard marine growth effects on the hydrodynamic behavior of a cylinder submitted to wave and current loading. *Ocean. Eng.* **2022**, *263*, 112194. [CrossRef]
69. Whelan, J.; Graham, J.; Peiró, J. A free-surface and blockage correction for tidal turbines. *J. Fluid Mech.* **2009**, *624*, 281–291. [CrossRef]