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Review

Tidal Stream Turbine Biofouling Detection and Estimation: A Review-Based Roadmap

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Abstract: In the context of harvesting tidal stream energy, which is considered a promising source of renewable energy due to its high energy density, stability, and predictability, this paper proposes a review-based roadmap investigating the use of data-driven techniques, more specifically machine learning-based approaches, to detect and estimate the extent of biofouling in tidal stream turbines. An overview of biofouling and its impact on these turbines will be provided as well as a brief review of current methodologies and techniques for detecting and estimating biofouling. Additionally, recent developments and challenges in the field will be examined, while providing several promising prospects for biofouling detection and estimation in tidal stream turbines.

Keywords: tidal stream turbine; biofouling; detection; estimation; data-driven techniques; machine learning

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1. Introduction

The oceans contain vast amounts of energy that could be harnessed for significant benefits. Ocean energy can help address climate change and promote sustainability, particularly for the 2.4 billion people living near coastlines. There are four main types of ocean energy, as illustrated in Figure 1 [1].

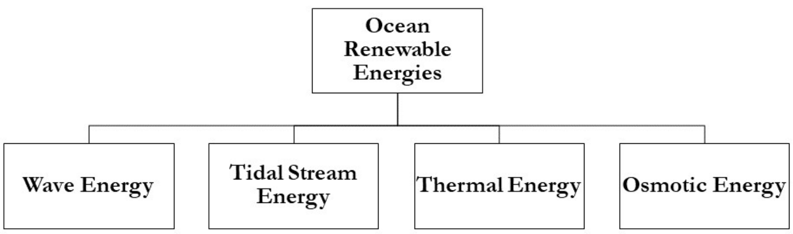


Figure 1. Types of ocean renewable energies.

Over the past decade, significant advancements have been made in the areas of tidal and wave energies, which are considered to be more reliable and consistent sources of power compared to solar and wind energy that can be affected by unpredictable weather. Tidal stream power, in particular, is an attractive option as it can be generated using submerged turbines, which have a minimal visual impact on the environment [2–6]. Unlike hydroelectric power plants, which rely on the flow of rivers, tidal energy harnesses the energy from ocean currents. In this context, Table 1 compares various renewable energy sources in terms of predictability, visual impact, environmental impact, and capital cost. Tidal stream energy offers advantages such as being a clean, predictable, and low-impact source of electricity. It does not produce greenhouse gases or toxic chemicals, it has low fluctuations in power generation, and its turbine farms have a minimal environmental impact.

Table 1. Comparison of various renewable energy sources [6].

Renewable Source	Predictability	Visual Impact	Environmental Impact	Capital Cost
Wind	No	High	Medium	High
Solar	No	High	Low	High
Hydro	Yes	High	Medium	High
Wave	No	Medium	Low	High
Tidal range	Yes	High	Medium	High
Tidal current	Yes	Low	Low	High

In 1967, the first commercial tidal power plant was built in the La Rance Estuary in Brittany, France. The plant had an installed capacity of 240 MW and was able to provide more than 5% of the region's domestic electricity demand. The plant's barrage was 720 m long and covered 22 km^2, and it also served as a road with a lock for shipping to pass through. The barrage featured 24 reversible 10 MW bulb turbines and a hydrostatic head of 5 m, and it had an annual power generation capacity of 480 GWh [7]. The Annapolis Royal Generating Station in Canada's Bay of Fundy was the second-largest commercial tidal power plant and was developed between 1980 and 1984. It has a capacity of 20 MW and generates 30 GWh per year [8]. The Shihwa tidal power plant, completed in 2011 in South Korea, is now the largest in the world [9].

The ocean power industry is expected to grow further in the future as many countries aim to reach net -zero emissions. As a result, many new projects are planned to use this technology for power generation [10]. Ocean energy is expected to become more widely used in the future, with large-capacity expansion plans predicted. As of 2020, there are wave and tidal stream projects in development with a combined capacity of 2.83 GW, as shown in Figure 2. According to the International Renewable Energy Agency, 10 GW of ocean energy may be commercially implemented by 2030 [11].

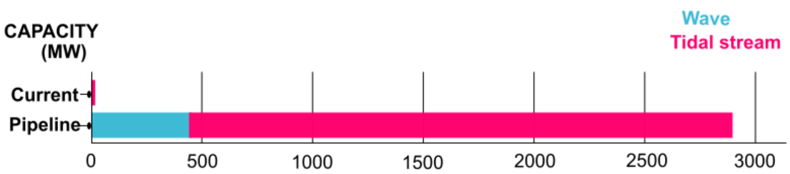


Figure 2. Active and projected tidal stream and wave capacity beyond 2020.

A significant challenge in the long-term use of Tidal Stream Turbines (TST) is their reliability in a marine environment. Biofouling, the buildup of organisms such as algae, mussels, and barnacles on surfaces, can negatively impact the performance of the turbine by altering its shape and roughness [12]. While the use of appropriate materials can reduce corrosion, controlling biofouling growth is more difficult. Biofouling on ship hulls has been well studied [13–19] , but there is limited research on its effects on TSTs [12,20–22] . To ensure optimal performance of the turbines, it is crucial to develop a specific biofouling management plan that allows for regular assessment and adjustments to reach the desired level of biofouling control. In other words, as TSTs performance degrades over time due to biofouling, it is critical to determine when the effects of fouling are significant enough to warrant removal. The purpose of this review-based study is to provide a thorough examination of the scarce available literature on the impact of biofouling on the performance of TSTs. It will also evaluate the pros and cons of various biofouling detection and estimation techniques, including a comparison analysis. This paper will identify areas of research that have yet to be explored and will suggest potential future research directions.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of biofouling and explores the relationship between TSTs and biofouling. Section 3 presents the latest advances in biofouling detection and estimation in TSTs. Section 4 provides an overview of the challenges and prospects in biofouling detection and estimation. Finally, Section 5 concludes the paper.

2. Biofouling vs. Tidal Stream Turbines

2.1. Biofouling Briefly

Biofouling is defined as the buildup of undesirable materials on a solid surface, leading to its impaired function. Specifically, marine biofouling refers to the accumulation of biological organisms on surfaces submerged in seawater. The process of biofouling begins with macromolecular conditioning and bacterial colonization, followed by the formation of a microfouling community composed of unicellular eukaryotes. This microfouling community can rapidly cover the substrate, though the timing can vary based on environmental factors. After a month of immersion, multicellular eukaryotes such as algal fragments and meroplanktonic larvae start to settle, leading to the development of a macrofouling community. These larger organisms eventually create a complex and advanced three-dimensional community on the substrate, as depicted in Figure 3 [12,20,23].

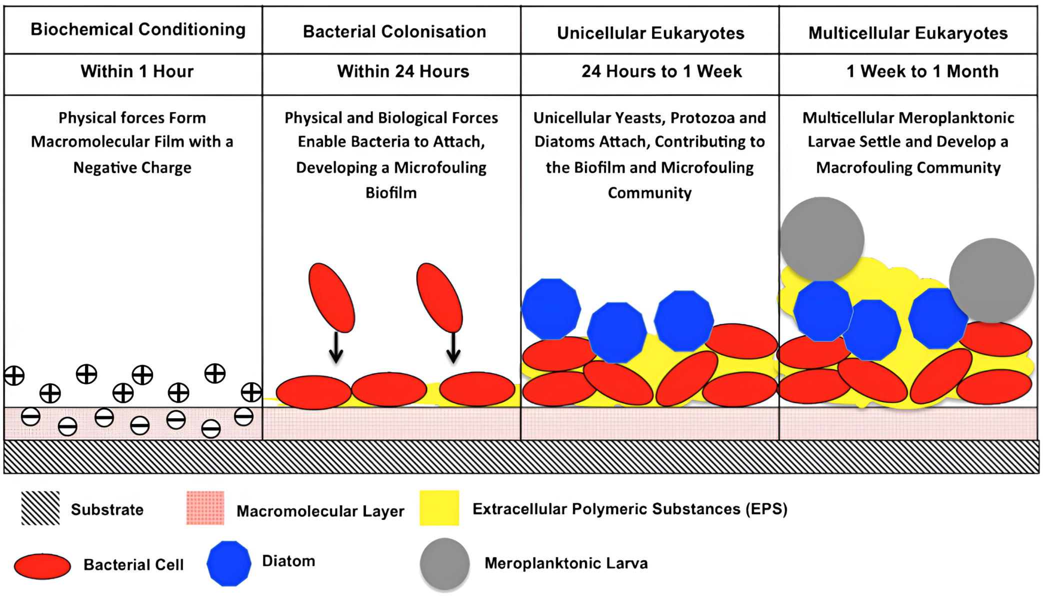


Figure 3. Diagram illustrating the process of biofouling accumulation on objects submerged in the sea. Reproduced from [23].

Organisms in a macrofouling community can be divided into two categories: hard and soft biofouling. Hard biofouling species, including tubeworms, barnacles, mussels, and tube-building amphipods, which construct either a protective shell or calcareous casing. On the other hand, soft biofouling creatures such sponges, anemones, hydroids, and sea squirts do not form shells or casings and often resemble jellyfish. It has been observed that prolonged installations of TSTs often experience significant biofouling, as depicted in Figure 4 which shows various fouling organisms attached to the turbine.

Figure 4. The Clear Current Company tidal stream turbine: Immersed in September 2006 and retrieved in October 2011 due to loss of performance. Reproduced from [20].

2.2. Biofouling vs. Turbine Technologies

Biofouling can impact the hydrodynamics of a TST, leading to an increase in drag and decreased performance [20,24,25]. This occurs as the biofouling buildup increases the resistance and creates recirculation loops and vortices near the blade surface, even if only partial colonization takes place [24]. The rotor of the TST can also be damaged by biofouling, which can have corrosive effects. Furthermore, the accumulation of marine fouling can accelerate the corrosion of the thin protective layer on the turbine blade [26] (Figure 5).

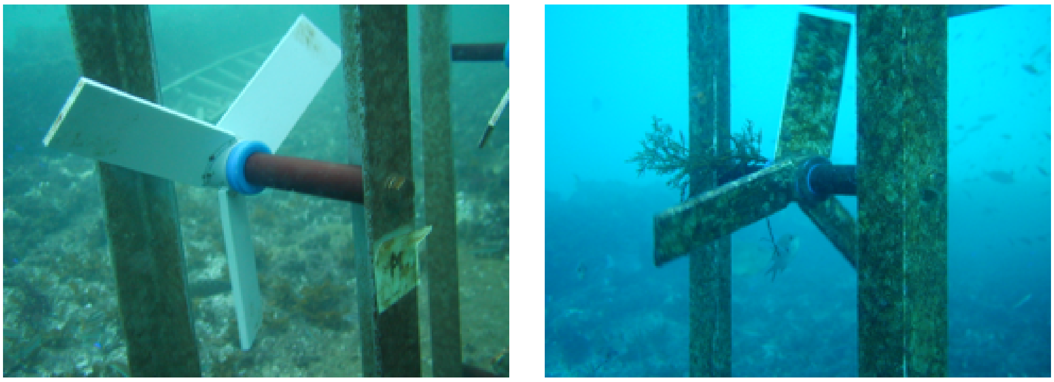
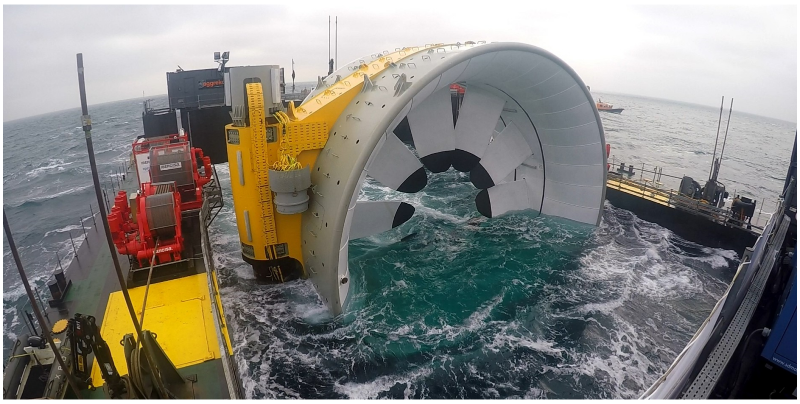


Figure 5. Illustration of the corrosion acceleration due to biofouling. Courtesy of Prof. Yusaku Kyozuka [27].

Tidal stream energy is mainly captured using horizontal-axis turbines that employ either geared or direct-drive systems, as shown in Figure 6 [28]. Both types of drivetrains have their own pros and cons, and the industry has not yet reached a consensus on the preferred technology [29]. In this context, the turbine technology, specifically its drivetrain option, will be more or less impacted by biofouling [29]. For instance, full direct-drive TSTs, due to their low-speed operation, often have large diameter generators and substantial static components that promote the development of biofouling, as depicted in Figure 4. In this case, the TST has been retrieved due to loss of performance. Figure 7 shows examples of well-known TSTs undergoing biofouling.

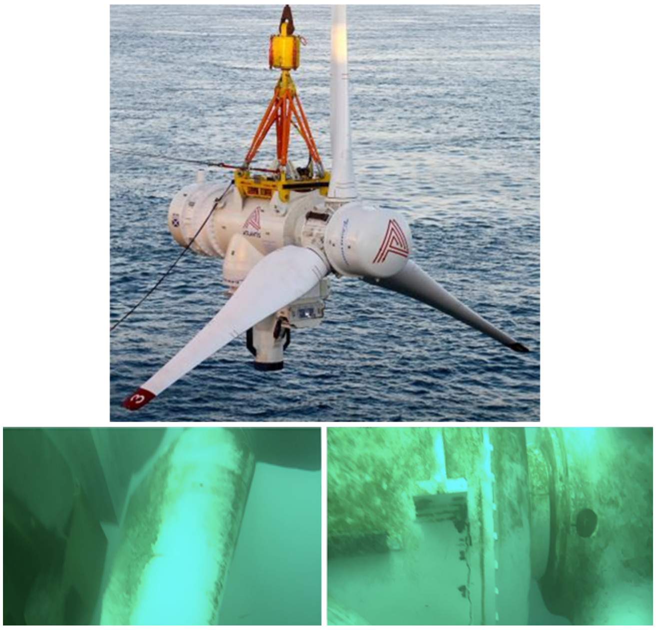
(**a**) SeaGen tidal stream turbine (geared turbine).



(**b**) OpenHydro tidal stream turbine (direct-drive turbine).

Figure 6. Horizontal-axis tidal stream turbines. Reproduced from [29].

(**a**)



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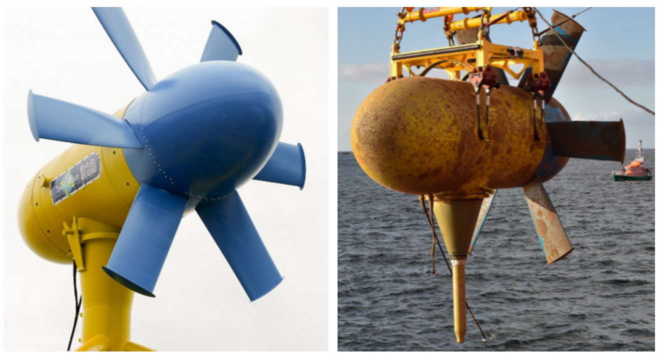


(**c**)

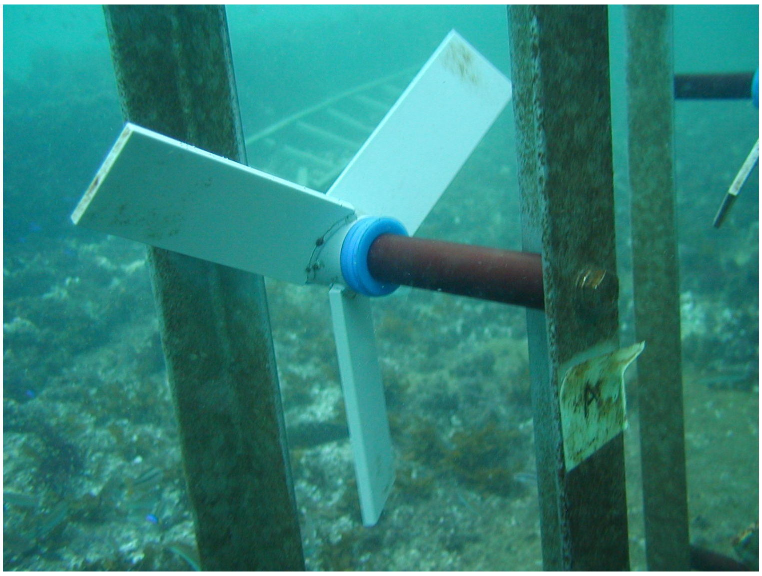
Figure 7. Biofouling accumulation illustrations. (**a**) The OpenHydro tidal stream case (turbine retrieved after 3 months of immersion). Reproduced from [30]. (**b**) The AR1000 tidal stream turbine case (ROV video monitoring). Reproduced from [31]. (**c**) The Sabella tidal stream case. Reproduced from [20].

There is currently limited operational experience in the marine renewable energy industry to make broad conclusions, but it is evident that submerged TSTs that are submerged for extended periods can experience a substantial buildup of marine growth, ranging from soft to hard, such as barnacles. This buildup is favored by the surface structure, with larger surfaces leading to a more significant buildup. As a result, the main conclusion that can be drawn regarding the TST drivetrain option is that a full direct-drive design (gearless) is more likely to promote biofouling development.

3. Biofouling Detection and Estimation

Efficient cleaning techniques for biofouling prevention rely on a detection process, but detecting biofouling is difficult due to its inherent unpredictability and related uncertainties, making it challenging to accurately predict its impacts on the monitored structure.

Early detection of biofouling, while it can still be removed, using environmentally friendly techniques that do not damage the paint or hull coating, is the most effective strategy for reducing biofouling. Figure 8 shows the significant impact of biofouling that can be avoided with an effective detection process.



(**a**) Biofouling inception.

(**b**) Highly impacting biofouling.

Figure 8. Illustration of highly impacting biofouling. Courtesy of Prof. Yusaku Kyozuka [27].

There are two main types of biofouling detection techniques in the literature: reporter-based and physical detection [32,33]. Physical detection studies the surface and monitors changes for early detection of biofilm growth (i.e., changes in transmembrane pressure or permeate flow through the membrane). Several imaging technologies, including light and epifluorescence microscopy techniques, electron microscopy, confocal laser scanning microscopy, and optical coherence tomography, are the primary vehicles for this strategy [34–37]. However, the monitored changes are only noticeable at the mature biofilm stage, making it difficult to effectively treat biofouling and limiting the effectiveness of cleaning. Detecting bacterial activity prior to full biofilm development (as shown in Figure 9) can help minimize the ongoing costs associated with biofouling and improve the efficiency of the system under consideration (e.g., ship, TST, floating offshore wind turbine, etc.). Reporter-based systems use cellular-level procedures to generate a measurable signal, such as enzyme-based cleavage or receptor-specific binding, which indirectly measures bacterial abundance with varying sensitivity. Extremely sensitive techniques such as flow cytometry, fluorescence in situ hybridization, and polymerase chain reaction can be used to count bacteria, but require extensive sample preparation, technical know-how, and lengthy incubation times (4–6 h) [38–40].

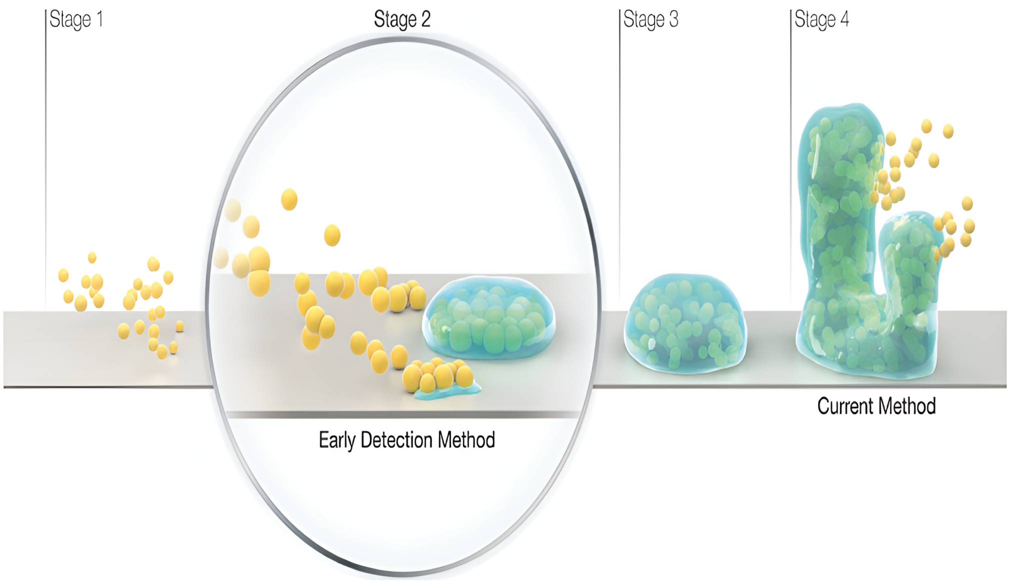


Figure 9. Biofouling development in an aqueous environment. Reproduced from [33].

Currently, biofouling detection is primarily conducted through the use of remotely operated vehicles or dive teams. The latter option requires working with a specific organization due to legal regulations to ensure safe diving practices, which results in longer inspection times, more staff, and typically subpar images and films that are used to interpret the overall condition of the monitored system. This method is also expensive, difficult to plan, and requires professionals to analyze the data, resulting in a lengthy report generation process. Image localization is also challenging to identify during post-processing. Alternatively, the use of a remotely operated underwater vehicle (ROV) is simpler in terms of equipment but still suffers from lengthy inspection and report generation times, with preparation taking around 3 h, inspection taking 6 h, and post-processing taking 10 h. Additionally, not all ROVs have adequate stabilization systems or high-definition imaging capabilities to ensure proper visibility and image quality [41,42]. A recent development in this field involves the implementation of reconfigurable magnetic coupling thrusters in the vectorial thrust of autonomous underwater vehicles. This technology offers improved water-tightness and enhanced maneuvering capabilities, which are highly desirable features in agile underwater vehicles used for visual inspection and maintenance of TSTs [43,44]. While the concept shows great promise, it is important to develop viable submersible prototypes that feature full waterproof mechanisms in order to effectively implement the technology.

3.1. What Was Done for Biofouling Detection in Vessels Hull and Propeller?

The issue of biofouling in ships is being addressed with the goal of improving operational efficiency and saving fuel or energy [45,46]. The goal is to reduce the frequency of costly cleaning, which can also lead to increased wear of the hull coating, resulting in higher resistance and fuel consumption. If the performance of the ship in service can be closely and accurately monitored, it may be possible to optimize the intervals for hull and propeller maintenance. Nowadays, ships are equipped with a variety of sensors that constantly record several variables, some of which reflect the hydrodynamic state of the vessel. These recorded variables can be used to monitor the hydrodynamic performance of the ship while in service [13,16,17].

In this regard, it has been proposed to use data-driven techniques, more specifically machine learning-based approaches, to analyze the in-service data recorded on board a ship and monitor its hydrodynamic performance over time [14,15,18]. Indeed, using data-driven models, advanced statistical techniques can be used to develop models based on historical data generated and stored by recording and monitoring equipment, without any prior knowledge about the physical phenomena behind the data. These data can be used for monitoring and fault detection purposes. In addition, data-driven models allow for the incorporation of exogenous data, such as weather conditions, which may contain valuable information that is difficult to represent by conventional methods [18].

A ship digital twin-based approach is a possible solution of choice to monitor biofouling development. In this context, authors in [19] developed a ship digital twin using the extensive data collected by the ship sensors. The main objective was to estimate the speed reduction caused by biofouling.

3.2. What about Tidal Stream Turbine Biofouling Detection?

Rotor blade failures in tidal turbines are of significant concern due to the effects of biofouling and the denser, more corrosive nature of seawater. From this perspective, it can be argued that biofouling may contribute to a type of turbine blade imbalance [47].

In this context, TST generator stator current-based analysis techniques are widely used because they allow for non-intrusive condition-based monitoring, which is ideal since it does not require additional sensors or data acquisition systems. These techniques involve the use of stator current signals to identify and quantify abnormal frequency excitations [48–55]. In [56], the authors have suggested the use of the stator voltage in the restrictive case where the generator is not connected to the grid and is unloaded. One shortcoming of signal-processing-based condition monitoring techniques is that they may be best suited for analyzing fixed-speed generators, whereas actual tidal turbine operations will typically involve variable speeds. In addition, imbalance faults typically result in cyclic impulses in the stator current. However, conventional time-series analysis is often inadequate in this case, as these impulses are often obscured by background noise or other undesired frequency components. To address this challenge, advanced signal-processing techniques are needed [49,51–55]. A critical analysis of TST biofouling blade unbalance main signal processing-based monitoring approaches are summarized in Table 2.

Table 2. Tidal stream turbine signal processing-based monitoring approaches critical analysis.

Ref.	Proposed Approach	Contributions	Limitations
[48]	Angular resampling	Proposes a method for detecting rotor imbalance faults in TSTs, with improved reliability and efficiency.	The process of resampling the sensor data at different angular positions and analyzing the resulting data can be computationally intensive, especially for large TST systems.
[49]	Variational mode decomposition (VMD)	This paper proposes a novel method for detecting rotor imbalance faults in TSTs using VMD and denoising techniques which improve the accuracy of the fault detection method to improve the detection accuracy.	The paper does not provide an in-depth analysis of the used denoising techniques. Further analysis of denoising techniques could help identify the optimal denoising method.
[50]	Concordia transform	Proposing an advanced concordia transform for blade imbalance fault detection by using TST generator stator currents.	The proposed method lacks analysis of false positive rates, which may increase the operating costs of the TST system due to unnecessary maintenance and repairs.
[51]	Wavelet threshold denoising	This paper proposes a method to detect imbalance faults in TSTs under different flow velocity conditions.	The generalizability of the proposed method to different TST systems and operating conditions is not clear, and further evaluation is needed to understand the performance of the proposed method under different scenarios.
[52]	Continuous wavelet transform	Extracting frequency-domain features from the vibration signals generated by the blades of marine hydrokinetic turbines which can be used to accurately classify the blades as healthy or faulty.	Does not provide a detailed comparison of the proposed method with other existing methods for detecting blade faults in marine hydrokinetic turbines.
[53]	Bispectrum analysis	This paper presents experimental results that evaluate TSTs stator currents bispectrum analysis in detecting biofouling.	A detailed comparison of the proposed method with other existing methods for detecting biofouling in TSTs is not provided.
[54]	Higher-order spectra	This paper proposes detecting blade biofouling in a TST using higher-order spectra analysis of the stator currents of its permanent magnet synchronous generator.	The study focuses solely on the use of higher-order spectral analysis to detect biofouling of TST blades while other types of spectral analysis, such as wavelet analysis, can improve its performance.
[55]	Data normalization and empirical mode decomposition (EMD)	The proposed method normalizes TST generator stator current signals and then applies EMD to identify the presence and severity of imbalance faults including wave and turbulence conditions.	The proposed fault detection methods assume the model parameters are known. However, in practice, these parameters are generally unknown and should be estimated. The potential benefits of using Ensemble EMD (EEMD) to improve detection accuracy have not been investigated.
[56]	Integration methodology	The proposed method integrates the features of the TST generator stator voltage signal to detect imbalance faults. The detection process is based on two main steps: data conversion using Hilbert transform and extreme value searching, and then the imbalance fault signature extraction using frequency sequences subtraction.	A detailed comparison of the proposed method with other existing methods for detecting biofouling in TSTs is not provided. In addition, it is yet to be demonstrated whether voltage can be effectively used for detection, given that TSTs connected to the distribution grid will an imposed voltage

Recent findings suggest that using machine learning algorithms to extract features from signal processing and statistical-based fault detection approaches can significantly improve their performance. Machine-learning-based approaches are particularly effective in identifying important trends that may be hidden by frequency interference and low signal-to-noise ratios in the TST generator acquired signals [57,58]. While in [57], authors used a hybrid approach that combines a physics-based model of the TST blades with machine learning techniques to detect imbalances, in [58], the generator power signal was used by the authors as a means of monitoring. Vibrations have also been investigated as means for monitoring [59,60]. In this context, it is suggested that further investigations are needed to fully evaluate the performance in real-world situations and to develop methods for improving the accuracy.

The significance of visual inspection for TSTs to ensure their safe and efficient operation has led to the proposal of using image processing as an effective alternative for monitoring biofouling. To achieve this, researchers have recommended using machine learning to extract features from processed images captured by an ROV [61–64]. However, several challenges have arisen in this context, particularly with regard to diagnosing biofouling types and estimating their thickness. Table 3 provides a critical analysis of machine learning-based monitoring approaches.

Table 3. Tidal stream turbine machine learning-based monitoring approaches critical analysis.

Ref.	Proposed Approach	Contributions	Limitations
[57]	Hybrid approach	Combines two existing approaches: physics-based modeling and data-based methods.	The effectiveness of the proposed method depends on the accuracy of the used physical model. If the model fails to accurately describe the behavior of the TST rotor blade under varying conditions, the fault detection accuracy may be reduced.
[58]	Continuous Morlet wavelet transform	Analyzing the generator power signal of the TST and using advanced signal-processing techniques to identify frequency components that correspond to rotor blade imbalances.	Fault detection methods based on generator power signal analysis may not be sensitive enough to detect small imbalances or faults in the rotor blades, especially in noisy environments or under varying operating conditions.
[59]	Sparse autoencoder and softmax regression	Combining modified sparse autoencoder and softmax regression for image processing to detect imbalance faults on the blade of a TST.	Training data amounts being limited, this may compromise the imbalance blade faults detection accuracy. In addition, the training process suffers from a significant computational load.
[60]	Bidirectional long short-term memory (BiLSTM) network	Proposing a BiLSTM network-based design for TST imbalance faults detection. In addition, a high-fidelity turbine simulation platform based on the NREL FAST code is developed for data collection and design testing.	The effectiveness of the proposed method may depend on the TST specific characteristics and operating conditions.
[61]	Coarse–fine semantic segmentation network	The proposed method combines coarse and fine branches using dynamic weights to effectively detect attachments, even under turbid conditions.	Evaluated on a relatively small dataset. However, it is not clear whether it can be generalized to larger and more diverse datasets.
[62]	Sparse autoencoder and softmax regression	Combining of sparse autoencoder and softmax regression techniques to extract and classify image features.	The proposed method relies on the availability of labeled training data that may not be readily available or that may require significant manual effort to obtain.
[63]	ShuffleNet v2	Improved version of the ShuffleNet v2 deep convolutional neural network that can accurately classify different types of attachment faults in real time.	The study did not explore the impact of different hyperparameters or training methods on the performance of the proposed method. Further optimization and development may be needed to improve the detection performance.
[64]	Depthwise separable convolutional neural network (DSCNN)	Extensive collection of images depicting different kinds of attachment faults in TST blades used to train and assess a DSCNN-driven detection approach.	It is assumed that the TST operates in steady state and does not consider the effects of transient conditions or dynamic loads on the detection process.

3.3. Biofouling Estimation

Accurate estimation of biofouling is essential to develop a reliable predictive maintenance prognosis method for tidal turbines. In this context, several well-known methods can be used to estimate the extent of biofouling [65]. These include: (1) Visual inspections of the TST surfaces can provide a rough estimate of the extent of biofouling. However, this method is subjective and can be time-consuming [66]; (2) Hydroacoustic uses sound waves to create images of the TST surfaces. These images can be exploited to estimate the amount of biofouling; (3) Laser scanning creates a 3D image of the TST surfaces. This method can provide highly detailed information about the extent and distribution of biofouling. This technique is typically costly and time-consuming; (4) Chemical analysis of the water surrounding the TST can provide information about the types of organisms present and their abundances. This method can be used to estimate the potential for biofouling. Unfortunately, all these monitoring methods are both time-consuming and expensive, resulting in a challenge for TSTs biofouling cost-effective and real-time monitoring.

In this context, performance monitoring of the TST can provide an indirect estimate of the extent of biofouling [67]. If the turbine power output decreases over time, it may be an indication of biofouling. The performance analysis involves measuring turbine power output and comparing it to expected values, which can be affected by biofouling. Variations in power output over time can indicate the extent and severity of biofouling, typically on the turbine blades. Performance analysis could be used in combination with other monitoring methods to provide a more complete picture of biofouling.

In a recent study [68], the development of an automated system for the assessment of biofouling in images in ship hulls has been discussed. The authors applied deep learning to automate the classification of images from in-water inspections to identify the presence and severity of fouling. They compared the results of the deep learning-based approach with those of three expert human assessors and found high levels of accuracy and precision. Furthermore, to address the methods issues of computational burden and related equipment cost, authors in [69], explored the feasibility of a hyperspectral imaging system for biofouling assessment. The system consists of a hyperspectral camera, a tunable light source, and a custom-built sample holder. The camera captures the reflected light from the surface, which is then analyzed using a wide neural network classifier to determine the type and amount of biofouling on the surface. The tunable light source enables the system to adjust the wavelength of the light to optimize the detection of different types of biofouling. These studies have important implications for the management of biofouling in TSTs, as an automated system could greatly improve the efficiency and accuracy of biofouling assessment. It also demonstrates again, as above-mentioned in section B, the potential of machine learning and image-processing techniques for biofouling monitoring and management.

4. Challenges and Prospects

TST biofouling detection and estimation can be challenging due to several factors, including:

Underwater environment. Indeed, TSTs operate in harsh underwater environments where visibility is limited and access for inspection and maintenance is difficult. This can make it challenging to detect and estimate the extent of biofouling on turbine components.

Biofouling variation. The nature and extent of biofouling on TSTs can vary considerably depending on factors such as water temperature, salinity, and flow rate. This makes it challenging to develop a universal detection and estimation method that works under all conditions.

Data processing. The data generated by sensors need to be processed and analyzed to provide useful information about biofouling on TSTs. This requires advanced data-processing techniques, including machine learning algorithms, to accurately detect and estimate biofouling.

Sensor selection. Choosing the right sensors, including cameras, to detect and estimate biofouling can be challenging. Different sensors have different sensitivities and resolutions, and the selection of the sensor needs to take into account factors such as the type and location of the biofouling.

Cost. Implementing a system for biofouling detection and estimation on TSTs can be expensive, requiring the installation of sensors and data processing infrastructure. The cost of the system must be carefully weighed against the potential benefits of reducing the impact of biofouling on turbine performance and lifespan.

In addition to these challenges, TSTs may face additional challenges related to their specific operating conditions, such as high turbulence and the presence of marine life [70]. These factors can make biofouling detection and estimation more difficult and require specialized sensors and data-processing techniques.

Despite these challenges, there are several promising prospects for detecting and estimating biofouling in TSTs, including:

Development of advanced sensors. The development of advanced sensors or a combination of sensors that can detect and estimate biofouling is a promising area of research. For example, sensors that use acoustic, optical, or electrical signals to detect biofouling are being developed and tested.

Machine-learning-based techniques. Machine learning algorithms are being applied to sensor-generated data to accurately detect and estimate biofouling. These techniques can improve the accuracy of biofouling detection and estimation and reduce the need for human intervention.

Regarding sensors development and combination, it has been already suggested that using different types of sensors, including generator current and voltage sensors, vibration sensors, and cameras, can provide a more complete and better picture of biofouling. In this context, videos, which are constructed using a stream of image is expected to be an interesting option for biofouling monitoring [68,71]. Indeed, the video format would offer the possibility of incorporating information from previous and future images to improve and smooth the biofouling estimates. One possible way to address the issue of limited visibility leading to blurry images is to utilize advanced sensors [61–64]. For instance, in [69], a solution was proposed using a combination of a hyperspectral camera, a tunable light source, and a custom sample holder. However, this approach may be considered impractical for TSTs and costly since poor image quality can be alternatively addressed through machine learning-based image-processing techniques.

Regarding data processing, particularly for biofouling monitoring, it is widely agreed that machine learning techniques are the most effective solution for addressing related issues with signal and or image processing.

In this context, to address the challenge of biofouling variation, typically identifying species or groups of species, two machine learning-based approaches can be adopted. The most challenging one is to consider local species by fine-tuning the developed model when deploying it in areas where no training data were collected and the fouling communities on the TST may be different to those in the training dataset [68]. This will likely improve the detection and estimation algorithm. An alternative approach to studying biofouling is to concentrate on categorizing the overall extent of biofouling coverage in an image, instead of solely identifying the species that are present as suggested in [68]. Indeed, using this approach eliminates the need for identifying individual species or species groups, which would have necessitated a much larger image dataset to achieve comparable outcomes. This approach should be most appropriate for monitoring biofouling of a tidal turbine, as the primary objective is to estimate the extent of biofouling for maintenance prognosis. Furthermore, the challenge of addressing the depth of biofouling through early maintenance can only be met by using images captured by multiple cameras. In this context, authors in [72] proposed a method for depth estimation from a single image, which uses additional sparse depth samples. The adopted end-to-end network processes both single image and sparse depth samples for estimating depth. The sparse depth samples are obtained using a low-resolution depth sensor or visual simultaneous localization and mapping algorithms. The proposed method, validated on various datasets and compared to other state-of-the-art methods, is a promising approach for estimating dense depth maps from a single RGB image and sparse depth samples.

The use of the video format makes it possible to improve and refine the biofouling estimates by incorporating data from previous and subsequent images. In particular, it is suggested to learn the spatiotemporal representation of motion information. This is however a difficult task that has been recently tackled in [73], where the authors proposed a long-term motion descriptor. In this case, the descriptor stream was introduced in a three-stream framework to identify the actions in a video sequence, therefore allowing a simultaneous capture of static spatial features, short-term motion, and long-term motion in the video.

Images and or videos could be useful and helpful for early maintenance purposes. Indeed, experiments conducted on a model ship have shown that barnacle settlement patterns can significantly affect ship resistance and powering, with some patterns resulting in a greater increase in drag and thus requiring more power to maintain speed [74]. In this case, these results can be used to inform the maintenance of TSTs, with particular attention to preventing and managing barnacle settlement in areas of the turbine where it is likely to cause the largest loss of performance (e.g., the blades).

With respect to the cost challenge, while focusing on categorizing the overall extent of biofouling coverage on a TST, performance monitoring should be preferred using the stator current of the turbine generator [53–55]. Such an approach will be more effective in detecting biofouling initiation. To improve the performance and accuracy of the estimation, image processing should be adopted as described above. In this context, data processing (current and image) should be performed using machine learning-based approaches. To enhance the accuracy and precision of detection and estimation, a data processing step for both current and image is suggested to handle the acquired signals such as noise and harmonics, as previously proposed for fault detection of electrical machines [75,76]. The conventional approach of feature extraction by learning, without a signal processing step, is widely adopted. However, it is not always clear how this method will perform with respect to the monitored system and potential failures.

Prompted by the success of incorporating machine learning into signal processing and statistical-based biofouling detection and estimation, it has been suggested to improve machine learning methodologies by incorporating prior physical knowledge through the incorporation of a physics-based loss function that mitigates inconsistent target labelling [57]. However, the modeling complexity can be overcome by a pure machine learning approach [77], although this remains a challenging task. In this context, in [78], it was provided with the most important challenges faced by data-driven prognostics and health management, including data availability, complexity, and drift to statistical heterogeneity, and system heterogeneity, while suggesting future directions to address these challenges. These prospective directions will help improve the monitoring of biofouling in TSTs, including their remaining useful life estimation [79].

The potential of digital twin technology with sensor-based techniques to improve the maintenance and reliability of offshore systems with a clear potential of application for TSTs condition monitoring [80–82] has recently been highlighted. Such a model-based approach will allow addressing the cost challenge. Specifically, utilizing a monitoring system based on digital twin technology offers a promising means of reducing costs while simultaneously optimizing turbine operation and maintenance [83,84].

In terms of prognosis [78], while following the TST current state (biofouling detection), the use of a digital twin will allow for predicting the future state (biofouling extent) during the TST using a machine learning-based monitoring approach [81].

5. Conclusions

This paper proposed a roadmap for using machine-learning-based techniques to detect and estimate biofouling in TSTs, which are a promising source of renewable energy due to their high energy density, stability, and predictability.

The proposed review covered various aspects, including the impact of biofouling on turbines, current detection and estimation methods, recent developments, and challenges. Furthermore, prospective advanced data-processing techniques, including machine learning algorithms, to detect and estimate biofouling in TSTs have been specifically discussed. These techniques should improve the accuracy and precision of detection and estimation, reducing the need for human intervention.

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