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Review

Numerical methods for monitoring and evaluating the biofouling state and effects on vessels' hull and propeller performance: A review

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ABSTRACT

Monitoring and evaluating the biofouling state and its effects on the vessel's hull and propeller performance is a crucial problem that attracts the attention of both academy and industry. Effective and reliable tools to address this would allow a timely cleaning procedure able to trade off costs, efficiency, and environmental impacts. In this paper, the authors carry out a critical review, accompanied with summary tables, of the biofouling problem with a particular focus on the shipping industry and the state-of-the-art techniques for monitoring and evaluating the biofouling state and its effects on the vessel's hull and propeller performance. In particular, different techniques are grouped according to the three main families of numerical models that have been designed and exploited in the literature: Physical Models (i.e., models relying on the mechanistic knowledge of the phenomena), Data-Driven Models (i.e., models relying on historical data about the phenomena together with Artificial Intelligence), and Hybrid Models (i.e., a hybridisation between Physical and Data-Driven Models). A conclusion from the performed review, open problems, and future direction of this field of research is detailed at the end of the review.

1. Introduction

The last decade has been characterised by growing concerns about greenhouse emissions and their increasingly apparent effects on climate change (Ritchie and Roser, 2020). The problem of global warming has been internationally recognised (IPCC, 2018) and has been one of the biggest drivers in most fields of current research and regulation. The shipping industry is no exception, and several promising technologies have been and are under development towards a net-zero carbon footprint (Anderson and Peters, 2016).

The increase in globalisation of trade comes partially as a result of a raising demand for the transport of resources (Hoffmann and Kumar, 2013). Shipping has been identified as the most efficient mode of transport to face this demand when compared to its land and air alternatives (Bouman et al., 2017). As a result, shipping has become responsible for 90% of global trade and a seemingly low, in comparison, global transport emission share of 2.9% (Buhaug et al., 2009; Smith et al., 2014; MEPC, 2020). This is due to a relatively low energy consumption and, therefore, a low cost per unit of carried weight (Owen et al., 2018), as well as a high degree of cargo safety (Seo et al., 2016). However, sulphur oxides, nitrogen oxides, particulate matter,

and carbon dioxide emissions due to shipping are still a significant contributor to air pollution (Coraddu et al., 2017).

Following the growth observed in the last 40 years (Bouman et al., 2017), the volume of waterborne transport work is expected to further increase, potentially doubling by 2030 (Ho-Chun Fang et al., 2013). Moreover, the shipping industry only recently started the uptake of new technologies (i.e., alternative fuels Gilbert et al., 2018; Balcombe et al., 2019) and still primarily relies on fossil fuel energy (Adland et al., 2018). Consequently, a rapid increase in shipping's Green House Gas (GHG) emissions volume and emissions share is expected due to the increase in transport volumes and the quicker decarbonisation of other industries (Chen et al., 2019). For example, the most recent Fourth GHG Study by the International Maritime Organisation (IMO) (MEPC, 2020) observed that the decrease in carbon intensity of shipping operations (i.e., due to the use of new technologies) was outweighed by the growth and total shipping emissions (i.e., due to the increase in waterborne transport volume). Specifically, emissions are still expected to increase from about 90% of 2008 levels in 2018 to 90–130% of 2008 emissions in 2050 for a range of possible scenarios (MEPC, 2020). As an attempt

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to rectify this, the IMO has been actively taking regulatory action. The development and enforcement of the EEDI (Energy Efficiency Design Index) by the Marine Environment Protection Committee (MEPC) and, since 2011, the requirement for ship owners to incorporate the Ship Energy Efficiency Management Plan (SEEMP) (MEPC, 2011) in line with the IMO are some examples of the IMO's efforts. Nevertheless, stricter regulations will be required in the future (such as the one on sulphur content requirements for marine fuel inside and outside Emission Control Areas (ECAs) Bilgili, 2021) to achieve the IMO's ambition towards a net zero environmental footprint of shipping by the end of the century, following a 50% reduction by 2050 (IMO, 2018).

The means of achieving the required emission reductions still remains an open question. In its second GHG study (Buhaug et al., 2009), the IMO suggests a combination of technological and operational improvements. The authors of Bouman et al. (2017) review a series of studies on ship energy efficiency increasing (and/or emission reducing) technologies and practices currently available in academia and industry. They reach the conclusion that a 75% reduction in emissions is possible by 2050 based on current technologies, including the adoption of alternative fuels. Unfortunately, they also state that widespread deployment of these technologies and practices is currently not happening fast enough or at the required scale. The authors of Rehmatulla et al. (2017) come to similar conclusions when analysing the implementation of over 30 candidate technologies. GHG reducing technologies (i.e., fuel cells, batteries, dual-fuel engines) and alternative fuels (i.e., ammonia and hydrogen) will have a substantial impact on the future (Bouman et al., 2017), but the current fleet cannot be realistically retrofitted in the short-medium term. For this reason, it is mandatory to keep current propulsion systems at their best efficiency. Improving vessel efficiency is also in line with ship owners' desire to reduce fuel costs, which often contribute to more than half of a ship's operational costs (Seo et al., 2016). In fact, an emission reduction of 33% by 2030 could be possible because most energy efficiency improving measures are cost efficient (Eide et al., 2011). Nevertheless, despite these being financially feasible, the adoption of new technologies is rare among vessel owners and operators. This is the so-called 'energy efficiency gap', which is caused by an unrealised potential for improvement, and affects many other fields (Johnson et al., 2014). Focusing our attention on the shipping industry, there are many factors causing this gap (e.g., safety, reliability, technological uncertainty, and market constraints) that act as a barrier for the implementation of new energy efficiency improving technologies (Acciaro et al., 2013).

Regardless of the emission reducing technologies employed, the vessel's hull and propellers are and will always be subject to performance decay. This loss in performance is mainly due to biofouling, namely the undesirable accumulation of microorganisms, algae, and animals on artificial surfaces immersed in seawater (Flemming, 2002). Effective maintenance can be responsible for up to 20% of total operational costs (Coraddu et al., 2019a) and, therefore, is a perfect candidate for optimisation and improvement. Moreover, effective maintenance of systems and system components reduces the disruptions that can be caused by faults or failures on-board (Tsaganos et al., 2020), ensuring that the vessel is operating at its best efficiency. Therefore, using intelligent tools as a decision-support instrument in maintenance planning is a potential source of operational improvements (Karagiannidis and Themelis, 2021). However, improvements need to be economically viable for vessel owners, as well as effective in reducing environmental impact (Halim et al., 2018). The majority of a vessel's energy consumption is employed to overcome the resistance associated with a ship's movement through water. This is directly linked to the roughness of the underwater ship surfaces. Direct exposure to seawater, which is both highly corrosive and filled with living organisms, is the main cause of surface roughness increases that negatively impact the hydrodynamic performance of a ship (Farkas et al., 2021a). This increase is responsible for higher GHG emissions due to the consumption of additional fuel, which is necessary in order to maintain a certain speed.

While novel systems that combat biofouling (Legg et al., 2015) are already available, two main methods of biofouling control are widely implemented (Flemming et al., 2009; Adland et al., 2018), namely, antifouling coatings and periodical cleaning. Nevertheless, no coating can fully stop biofouling (Oliveira and Granhag, 2016) and the coating needs to be periodically replaced during dry-docking. Additionally, periodical cleaning is a time-consuming and costly maintenance activity. For this reason, being able to monitor and evaluate the biofouling state and its effects on vessels' hull and propeller performance is of paramount importance. Unfortunately, due to the dynamic and multi-faceted nature of the problem, this remains a difficult task (Farkas et al., 2021b). Throughout the years, researchers have attempted to develop numerical methods which can effectively be used as a guide for maintenance strategies. In the current work, the authors critically review the state-of-the-art of such methods. The review is supplemented by summary tables grouping different approaches according to the three main numerical modelling approaches present in research: Physical Models (PMs) (i.e., models relying on the mechanistic knowledge of the phenomena), Data-Driven Models (DDMs) (i.e., models relying on historical data about the phenomena together with Artificial Intelligence), and Hybrid Models (HMs) (i.e., a hybridisation between Physical and Data-Driven Models). A conclusion from the performed review, open problems, and future direction of this field of research is detailed at the end of the current work.

The rest of the paper is organised as follows. Section 2 provides a comprehensive description of the biofouling problem. Section 3 outlines the preliminaries for the review of numerical methods for monitoring and evaluating of a vessel's biofouling state and its effects. A critical analysis of existing work is reported in Section 4. Section 5 summarises the open problems and future perspectives of this important field of research. Finally, Section 6 concludes the review.

2. The biofouling problem

A large body of research has been devoted to analysing the impact of biofouling and mitigating its effects on vessel powering and performance. To better understand the numerical model, it is worth describing the biofouling phenomenon in more detail.

2.1. Biofouling definition

Biofouling is an unwanted process, characterised by several stages of formation, which results in the growth of marine life on a ship's wetted surfaces. According to Townsin (2003), ship hull biofouling can be characterised by three categories: weeds, shells, and slime. The former two are referred to as macrofouling and the latter as microfouling. Macrofouling forms on vessels with longer nonoperational periods and has more pronounced negative effects on ship performance (Koboević et al., 2019). Instead, ships with high operational speeds and low periods of down time commonly experience earlier and less detrimental stages of biofouling, such as the formation of a biofilm and the growth of algae, also termed as microfouling (Koboević et al., 2019; Farkas et al., 2020b).

The initial biofouling stage is the formation of a slime film with varying thickness, depending on the growth stage. Once a biofilm has been formed, its presence makes the further growth of weed and shells much easier (Candries et al., 2003). This development is not uniform over the vessel's entire underwater surfaces (Adland et al., 2018): the separate regions of an underwater body experience varying conditions, for example in terms of fluid flow, due to the general non-uniformity of a ship hull, providing different levels of facilitation for organism growth. Moreover, this development also varies between vessel types and missions, depending on their operational characteristics (Davidson et al., 2020). In fact, navy ships often spend long periods in port, whereas commercial vessels rarely remain stationary for a prolonged period of time due to their need to complete transport work in order to
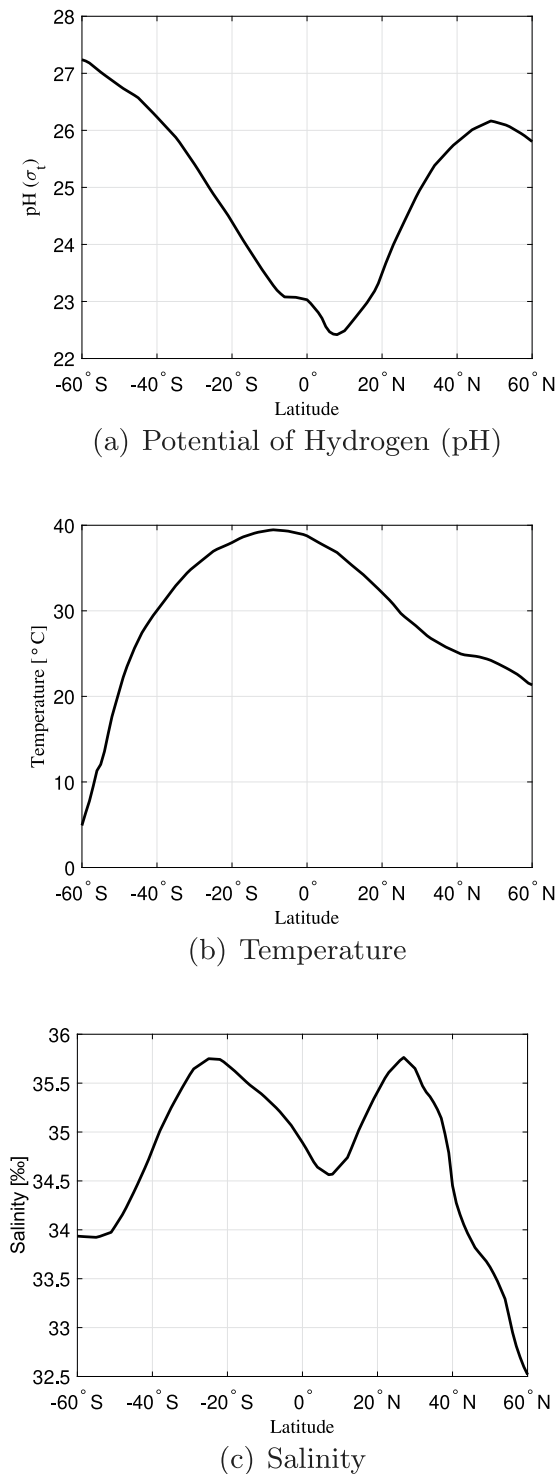
Biofouling organisms thrive in warmer weather (Adland et al., 2018), which not only means that there is a geographical influence on their development, but also seasonal variations. In fact, examples of water temperature, salinity, and pH as a function of latitude are reported in Fig. 1. The majority of marine lifeforms prefer steady environmental conditions, therefore, fewer organisms are able to survive on the submerged surfaces of vessels whose operation involves rapid and frequent changes in environmental conditions (Koboević et al., 2019).

2.2. Biofouling impacts

Biofouling results in severe drawbacks and dangers (see Fig. 2). In particular, it negatively impacts vessel efficiency in terms of performance and costs (Hewitt et al., 2009) (see Sections 2.2.1 and 2.2.2), as well as resulting in damages to the environment when combined with the global nature of shipping (Moser et al., 2016) (see Section 2.2.3).

2.2.1. Performance impact

In order for a vessel to move through water at a certain speed, its propulsion system must generate an appropriate amount of thrust, which overcomes the inherent resistance associated with this movement. The total experienced resistance is a combination of several components concerning friction, as well as pressure variations due to wind, waves, and the hull's movement through water (Atlar et al., 2018). The biggest and most influential contribution to the total resistance (up to 90% according to Schultz, 2007) is the skin friction of a vessel's underwater hull. It originates from the viscosity of water and is directly affected by the smoothness/roughness of the underwater surfaces of a ship. Thus, it is easy to observe that the condition of a vessel's hull, propeller, and other appendages has a direct correlation with this important frictional element of the total resistance. Biofouling has a negative effect on the roughness of the subjected surface, resulting in an altered hydrodynamic profile and a higher total resistance.

The negative impact of an increase of the hull's resistance due to biofouling can be evaluated in two ways (Farkas et al., 2020b). To maintain a desired speed, there must be an appropriate increase in the delivered thrust by the propulsor, i.e. there will be a higher power demand. If the delivered power is to be maintained, the increase in total resistance due to biofouling results in a natural decrease of the vessel's speed. Additionally, if the former perspective is taken into account, the increase in delivered power can also be considered with regards to fuel economy. These different evaluation methods exist in literature, making it difficult to easily compare the results of different research works (Adland et al., 2018).

Each of the mentioned biofouling stages is different with regard to the scale of its negative impact on a vessel's performance (Schultz, 2007). Even the formation of a slime film has a pronounced impact on hydrodynamic performance. For example, Watanabe et al. (1969) reported an 8÷15% increase of frictional resistance due to the presence of slime. This has been further confirmed by Farkas et al. (2020b) where a Computational Fluid Dynamics (CFD) implementation was exploited to determine the impact of different stages of slime film development. An increase in total resistance ranging from 0.5 to 25.8% was observed when different biofilm stages were examined. Moreover, in Schultz (2007) the effects of biofouling on ship resistance and powering were studied and it was discovered that a light slime film resulted in around a 10% increase in shaft power and total resistance, whereas heavy slime films could result in around a 20% increase.

Macrofouling affects the total resistance to a greater extent. The estimation of added resistance due to weed biofouling is difficult and of minor interest (Townsin, 2003). Instead, the impact of hard calcareous fouling on hull resistance, propeller performance, and propulsion characteristics is often the subject of research in the field. For example, (Kempf, 1937) conducted an experimental campaign on pontoons with varying coverage and height of shells with the goal of predicting added resistance due to biofouling. In Demirel et al. (2017) towing

Fig. 1. Variation of environmental factors with latitude affecting biofouling process (Yebra et al., 2004).

remain profitable. Therefore, a container carrier, that often completes long voyages at constant high speeds, most likely will experience the onset of fouling to a lesser extent when compared to a sedentary navy ship (Koboević et al., 2019). Finally, the vessel's operational envelope has a substantial influence on biofouling. Environmental variables (e.g., water temperature, salinity, pH, nutrient composition, flow velocity, depth, and light) affect the properties of biofouling (Uzun et al., 2019; Yebra et al., 2004).
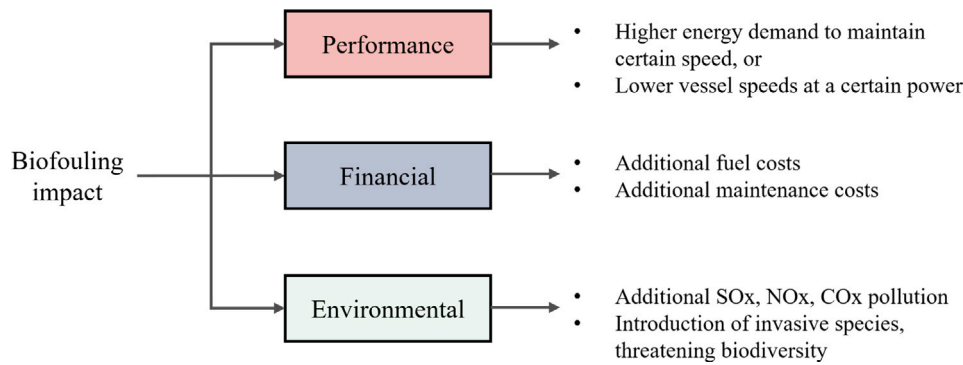
Fig. 2. Biofouling impacts.

Table 1
Performance impact of biofouling.

Ref.	Method	Microfouling impact	Macrofouling impact
Watanabe et al. (1969)	Rotor and Towing tank experiments	Frictional resistance increase 8 ÷ 15%	N/A
Farkas et al. (2020b)	CFD	Total resistance increase 0.5 ÷ 25.8%	Total resistance increase 50 ÷ 120%
Schultz (2007)	Laboratory-scale drag measurements and boundary layer similarity law analysis	Total resistance increase of around 10% for a light slime film and around 20% for a heavy one	Total resistance increase ranging from 35 ÷ 86%

tank experiments using flat plates covered with artificial barnacles of varying size and coverage were performed. The results, extrapolated at full-scale, showed that barnacle size has a significant effect on added resistance due to biofouling, where a 10% coverage with 10mm diameter and 5mm height artificial barnacles led to the same 44.6% increase in effective power requirement that was observed for a 50% coverage with 2.5 mm diameter and 1.25 mm height shells. The above results confirmed the assumption of Schultz (2004) that the height of the largest barnacles (part of a fouling layer) has the largest impact on drag. In Schultz (2007) an increase of required shaft power between 35% for lesser and 86% for heavy calcareous fouling was reported. This was observed at cruising speed through a method of predicting the effects of coating roughness and fouling on a full-scale ship by utilising model tests. Finally, the authors of Farkas et al. (2020b) exploited CFD simulations with varying extents of hard fouling on different ship and propeller types to determine the impact of hard fouling on ship performance. They observed increases in total resistance in the range between 50 ÷ 120% across different hull forms, along with increases in required delivered power between 75 ÷ 213.4%.

For the sake of completeness, a brief summary on the performance impact that has been attributed to biofouling is reported in Table 1.

2.2.2. Financial impacts

As discussed in the previous section, over time biofouling decreases the efficiency of a vessel, requiring additional fuel for achieving the same mission. An increase in the fuel quantity required for powering is accompanied by extra financial strain. In fact, 60 ÷ 70% of the operational costs of a ship result from its energy requirements (Rehmatulla and Smith, 2015). There is a direct monetary cost to maintaining a fouling-free vessel, as well as accompanying down periods, where the vessel is unable to perform its mission (see Fig. 3). Therefore, there is an obvious trade-off between the costs of hull and propeller maintenance activities and the costs due to increases in total resistance. In fact, it is crucial to develop tools which are able to effectively estimate the loss in efficiency (and the increase in costs) due to the vessel's biofouling state in order to detect the optimal point in time for conducting hull and propeller maintenance (Coraddu et al., 2019b). The most influential and widely known study to address the financial aspects of ship fouling
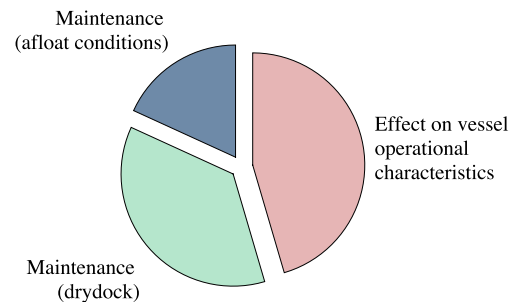

Fig. 3. Economic impact of biofouling.

is that done by Schultz et al. (2011). An in-depth analysis and breakdown of the costs associated with the fouling of an entire class of naval vessels allowed the researchers to quantify the financial expenditure that is needed to combat the usual performance deterioration with time. The above lead to a conclusion that even modest improvements in the fouling condition of a hull could save enough money to cover the costs of development, acquisition, and implementation of even relatively expensive technical or management solutions.

The financial aspects are not only ground for the creation of tools and strategies which can help fouling management, but there is also a need and desire for such developments (CSC, 2011).

2.2.3. Environmental impacts

As stated in the introduction, the energy efficiency gap in Maritime is a serious problem that needs to be addressed. The overall efficiency decrease due to biofouling has a severe environmental impact caused by the increase in the amount of pollutants expelled to the atmosphere through exhaust gases. The IMO has previously estimated that the deterioration in hull and propeller performance of the world fleet is accountable for 9 ÷ 12% of GHG emissions (IMO, 2011). Being able to assess the vessel's performance decrease due to fouling in real-time and, subsequently, to use this information to improve current maintenance practice then becomes fundamental. Moreover, these tools

are inexpensive and relatively easy to exploit on both old and current vessels. In fact, researchers have been able to achieve this using Noon Reports (NR) (Pedersen and Larsen, 2009a) which are widely available for most ships and even if not, their creation is solely dictated by company operational practice.

Another aspect to take into consideration is that a single vessel can travel across very long distances and often connects geographical locations with entirely different marine life, becoming a vector for the transportation of species across the globe. This becomes a problem when considering potentially invasive organisms, which threaten the biodiversity of the oceans. In fact, there is evidence that fouling is even more likely to cause the transfer of foreign species than ballast water (Sylvester et al., 2011; Chan et al., 2015). The chance of spreading non-indigenous species through fouling has been observed to increase with the age of the hull and propeller's antifouling coating (Chan et al., 2015). Interestingly, microfouling is far less likely to result in the spread of non-indigenous species when compared to macrofouling because the organisms that slime films are comprised of lack reproductive structure (Chan et al., 2015). Maintaining a vessel's hull at earlier stages of fouling development, while also collecting the resultant waste, could be considered as a viable option in reducing this environmental risk (Schultz et al., 2011; Adland et al., 2018).

2.3. Fouling control

To mitigate biofouling's negative effects, two main means of mitigation and control are used in combination.

Antifouling coatings are normally applied to the exposed surfaces of ships to protect against, or at least slow down, the build-up of biomass. Different coating technologies exist, utilising different approaches. As described by Uzun et al. (2019), the main ones are Self-Polishing Copolymers (SPC), Controlled Depletion Polymers (CDP), and Foul-Release coatings (FR), which can be further split up into biocidal (SPC and CDP) and non-biocidal (FR). Ultimately, the former release chemicals to prevent the formation of biofouling, whereas the latter reduce the attachment strength of marine life and facilitate the release of biofouling from treated surfaces when the vessel is moving. Biocidal coatings have a long history of environmental damage: for a long time tributyl tin (TBT) was used industry-wide because of its very high effectiveness in preventing fouling, however, was ultimately banned due to its serious environmental impact (Townsin, 2003) and replaced with copper-based biocidal coatings. However, these are now also being banned regionally (Townsin, 2003). Hard coatings, on the other hand, have been found neutral to the ocean with a lifespan of at least 10 years, where they may even extend the life of the hull (Song and Cui, 2020). None of the technologies mentioned above provide full protection (i.e., biofouling still occurs on the hull and propeller of vessels). The application of antifouling coatings only reduces fouling accumulation between cleaning events and allows for longer periods between them (Oliveira and Granhag, 2016).

Manual cleaning of the hull and propeller is the second method of fouling control, which can either be done underwater by divers with specialised brushes and Remotely Operated Vehicles (ROVs) or when the vessel is dry-docked (Song and Cui, 2020; Morrisey and Woods, 2015). Dry-docking is the more effective of the two methods as it allows for cleaning, sandblasting, and re-coating of the hull with a new antifouling coating and results in a larger reduction in total resistance (Adland et al., 2018). Moreover, it is the only method which allows for the neutralisation of invasive species (Adland et al., 2018). Unfortunately, dry-docking is also expensive and thus is undertaken only when necessary, usually every 3 to 5 years (Hua et al., 2018). Underwater cleaning of the hull and propeller has been observed to have roughly half the beneficial effect on reducing fouling resistance when compared to dry-docking (Adland et al., 2018), however, it is much cheaper. In fact, in Haslbeck and Bohlander (1992), authors state that underwater cleaning costs would get accounted for in between 14 and 24 operational hours through fuel savings. The replacement of divers with specialised ROVs for underwater cleaning can be identified as another option (Bohlander and Zealand, 2009). Unfortunately, for foul-release silicone coatings, underwater cleaning is not suitable (Foteinos et al., 2017). Additionally, it also does not allow for the collection of biological waste and can lead to the rapid discharge of antifoulants from biocidal ship hull coatings, which without proper filtration can cause severe environmental damage (Scianni and Georgiades, 2019). For this reason, classic underwater cleaning is banned in many ports across the world (Koboević et al., 2019). Nevertheless, methods for addressing the shortcomings of underwater cleaning, namely capture technology, are currently under development (Tamburri et al., 2020). Additionally, underwater cleaning is often combined with hard coatings which avoids the discharge of toxic particles (Song and Cui, 2020).

3. Preliminaries

Before reviewing the methods available in the literature, in this section, a concise explanation of biofouling-related parameters and collectable data useful for monitoring and evaluating the relevant effects on hull and propeller performance is provided. In fact, it is important to have a clear understanding of what phenomena can be measured or simulated by means of endogenous (i.e., vessel specific) or exogenous (e.g., environmental) data collection. Specifically, a parameter is referred to as exogenous if it is determined outside of a vessel's operation and cannot be influenced by the examined system, whereas endogenous measurements describe factors over which there is control. For example, environmental conditions are exogenous as they describe the environment in which the ship has to operate and cannot be influenced. In fact, exogenous parameters are the main subject of filtering because of the inherent difficulty of estimating their effects on a vessel. Knowledge about exogenous parameters is extremely valuable because it allows approaches to take the influence of outside conditions into consideration, irregardless whether this is done as part of a deterministic approach for evaluating added resistances due to wind, waves etc., or as part of a data-driven approach where the phenomena are captured in a purely artificial way.

For this reason, the data that can be available is first described, followed by what quantities it is possible to estimate for the purpose of monitoring and evaluating biofouling effects on hull and propeller performance.

3.1. Available data sources

The quality, volume, and variety of collected data varies between vessels and is highly dependent on the particular equipment installed on board (Cheliotis et al., 2020). Due to the long life cycle of ships, data recording capabilities vary substantially, depending on a ship's age (Rødseth et al., 2016). Retrofitting sensory equipment is an option which many ship owners actually pursue (Lim et al., 2019). Considering the task of vessel's operational monitoring, for both newbuilding and retrofitting, selecting the array of sensors is a complex ship-specific problem, which depends on the particular monitoring application, the shipowner's needs and the desired capabilities (Kaminaris et al., 2014). In fact, many different metrics need to be taken into account, such as the cost of the sensors and their probability of failure, the costs and the complexity of the installation, and the estimated benefits (e.g., environmental, economical, etc.) (Lim et al., 2019). The final array of sensors available for the vessel's monitoring directly affects the condition monitoring system's capabilities, quality, and accuracy (Dalheim and Steen, 2021). As a matter of fact, collecting high frequency and quality operational data facilitates the development of enhanced monitoring capabilities but, at the same time, increases the cost of the installation, maintenance, and operation of the monitoring system itself (Raptodimos et al., 2016). Most commonly, it is required to exploit, in an opportunistic way, all the measures and sensors already

Table 2

Typical biofouling-related operational measurements.

Parameters	Description	Source	Sensors	Reliability
Water Depth	The value of a water depth measurement in terms of vessel performance modelling comes with respect to estimating shallow water effects. With decreasing water depth, these become more impactful	Exogenous	Depth sounder (also called echo sounder or depth finder) or Pressure-based depth sensor	High
Water Properties (e.g., Temperature, Density, Viscosity, and Salinity)	Variations in water properties directly affect the hydrodynamic performance of a vessel	Exogenous	Various sea water sensors	High
Sea State Properties	Knowledge of the sea state allows for the estimation of wave effects on the ship	Exogenous	Shipboard sensors, Satellite data or Wave buoys	Medium/ High
Water Current Properties	Knowledge of the water current speed and direction with respect to the vessel could allow for the use of speed over ground instead of speed over water (SoW). This helps curtail the low reliability of SoW measurements.	Exogenous	Acoustic Doppler current profilers	High
Wind State Properties	Knowledge of the wind state allows for the estimation of wind effects on the ship.	Exogenous	Anemometer	High
Air Properties (Temperature, Pressure, Humidity etc.)	Variations in air properties directly affect the aerodynamic performance of a vessel.	Exogenous	Shipboard sensors such as temperature sensor, barometer, humidity sensor etc.	High
Draft & Trim	Draft & Trim are key hydrostatic properties, which directly affect hydrodynamic performance.	Endogenous	Hydrostatic level sensors in multiple locations across ship length	High
Vessel Speed through Water	Speed through water (also LOG speed) helps determine a vessel's operational efficiency and rate of fuel consumption. It is complicated to calculate accurately, requiring knowledge of currents and other forces acting on the vessel.	Endogenous	Paddle wheel speed sensor, Ultrasonic speed sensor, Electromagnetic speed sensor or, most recently, Doppler log which is more accurate	Medium/ High
Vessel Speed over Ground	Speed over Ground (also GPS speed) is the speed at which the vessel moves with respect to its geographical position.	Endogenous	GPS signal	High
ME RPM & Torque	The power output of the engine through its RPM and Torque indicates operational setting.	Endogenous	Rotational speed sensor (for example a tachometer) and a Torque sensor	High
ME Fuel Consumption	Fuel is the source of propulsive power and so it is directly linked to energy efficiency.	Endogenous	Mass flow metre	High
Fuel Properties	Fuel properties such as heating values, density, temperature etc. vary and are important parameters related to the energy input into the power plant.	Endogenous	Fuel quality sensor & Fuel heating value sensor	High
Shaft Torque, RPM and Power	The shaft power is a good indicator of the power available for propelling the vessel.	Endogenous	Shaft power (torsion) metre	Medium/ High
Propeller Thrust	A propeller's generated thrust is the vessel's moving force, which opposes total resistance.	Endogenous	Thrust metre, usually an optical sensor	High
Propeller Pitch	The propeller's pitch sets its operational point. For a vessel with a controllable pitch propeller, this can be varied.	Endogenous	Propulsion Control System	High
Rudder Angle & Activity	Angling the rudder results in a sideways force, which turns the vessel. Rudder activity also results in power losses i.e. added resistance.	Endogenous	Rudder angle sensor	High

available and still obtain good results without investing in retrofitting or modifying newbuilding projects (Koboević et al., 2019). Note that, some information, can be also retrieved via virtual sensors which do not require any physical sensor installation (Lim et al., 2019). Although virtual sensors might lead to less accurate estimation, this approach still provides some benefits of having a physical sensor without the associated capital cost (Costantini and Susstrunk, 2004).

Table 2 briefly reviews the biofouling-related operational measurements as well as example sensory equipment. Some sensory features are inherently less reliable than others due to the nature of the target parameter and the nature of the sensor exploited (Ikonomakis et al., 2021). A lot of variables are not included (e.g., light intensity, water nutrient composition, and water pH etc.) despite them being influential in terms of the speed and type of biofouling formation, partially because of the difficulties associated with their measurement (Uzun et al., 2019). Moreover, the current work is focused on methods for determining the biofouling performance impact rather than the specifics of the biofouling growth process.

3.2. Parameters to estimate

For what concerns the scope of this review, the most important parameter to estimate is the impact that biofouling has on the vessel's hull and propeller performance. In particular, it is often required to compare the actual 'real-life' performance with the base case when the hull and propeller are 'clean' (i.e., not fouled) (Brandsæter and Vanem, 2018). Commonly, data recorded during ship sea trials is used to represent this unfouled scenario (Coraddu et al., 2019a; Foteinos et al., 2017; ISO, 2016a,b,c). Nevertheless, this approach is not always the correct one since, in time, other vessel components are subject to decay (Liang et al., 2019) and this may lead to an overestimation of the biofouling effects on hull and propeller performance. Additional vessel fuel consumption is usually exploited to translate the added resistance due to biofouling into a measure that can be easily converted into a monetary cost (Schultz et al., 2011). However, due to many other exogenous factors that can potentially influence the fuel consumption,

Table 3
Typical parameters for biofouling impact estimation.

Ref.	Parameter	Link to shipping practice
Coraddu et al. (2019b), ISO (2016a,b,c), Koboević et al. (2019), Farkas et al. (2020b), Logan (2012), Erol et al. (2020), Karagiannidis and Themelis (2021)	Speed loss	Can be translated into longer voyage times and bigger delays in schedule.
Koboević et al. (2019), Coraddu et al. (2019a), Adland et al. (2018), Farkas et al. (2020a,b)	Additional fuel consumption	Direct connection to increased fuel costs and, therefore, operational costs.
Pedersen and Larsen (2009a), Uzun et al. (2019), Demirel et al. (2017), Farkas et al. (2020b), Atlar et al. (2018), Schultz (2007), Foteinos et al. (2017), Demirel et al. (2019), Song et al. (2020c), Schultz et al. (2011), Logan (2012), Foteinos et al. (2017), Demirel et al. (2017), Uzun et al. (2019), Song et al. (2020a), García et al. (2020), Senteris et al. (2019), Laurie et al. (2021), Karagiannidis and Themelis (2021)	Additional power requirement/Added resistance	Can result in overloading of the vessel's engine and is indicative of higher energy needs/lower ship efficiency.
Song et al. (2020b), Farkas et al. (2021b)	Change in propeller open-water performance (i.e Thrust coefficient, Torque coefficient & efficiency)	Indicative of a shift in propeller performance envelope and can be used to guide modifications towards optimal vessel operation.

it has been proven to be inaccurate for describing the added resistance due to biofouling (Carchen and Atlar, 2020). In fact, Carchen and Atlar (2020) argue the need for new measures (in addition to speed loss, added power requirements and fuel consumption) which provide enhanced insight into vessel hydrodynamic performance changes due to biofouling. Specifically, they propose three novel parameters, i.e., hull viscous drag, effective wake, and propeller sectional drag, which have the potential to improve the ability to evaluate biofouling's impact on ship hydrodynamic performance. Nevertheless, these parameters are difficult to relate to commercial shipping practice. For example, the use of simpler parameters such as speed loss is useful in translating the delay in vessel operations into financial losses (Coraddu et al., 2019b). The same can be said regarding increases in power and fuel requirements (Schultz et al., 2011).

Table 3 summarises the main parameters that are usually estimated and exploited to measure the biofouling impact.

3.3. Modelling approaches

To estimate the parameters described in Section 3.2 based on the data described in Section 3.1 the most effective and cost-efficient approach is to use numerical methods (Carchen et al., 2019). These numerical models can build upon the physical knowledge of the problem (Farkas et al., 2020b), or on historical data about the biofouling phenomenon (Coraddu et al., 2019b), or on both (Coraddu et al., 2021). According to what type of information is used to formulate the model, physical knowledge of the problem and/or collected historical data, the construction of the model changes. In particular, three different types of modelling approaches can be identified: Physical models (PMs), Data-driven models (DDMs), and Hybrid models (HMs). PMs are built based on a-priori, mechanistic knowledge of the real system (i.e., the numerical description of the biofouling growth and related added resistance) (Carchen et al., 2019). DDMs, instead, are built based on historical collections of observations of the vessel in operation (i.e., vessel speed, fuel consumption, delivered power, wind, waves, sea currents data), exploiting state-of-the-art Machine Learning (ML) techniques (Coraddu et al., 2019b). In the case of an HM, the PM and the DDM are combined to build models which use both a-priori physical information of the underlying phenomenon and historical data (Haranen et al., 2016). Fig. 4 reports a graphical representation of these three modelling approaches and how they are built.

Since PMs are based on the knowledge of the physical laws governing the phenomenon, they can be very reliable. In fact, by construction, they only produce physically plausible predictions. The expected accuracy of the results grows with the increase of the detail in modelling the physical phenomenon (Atlar et al., 2018). However, usually, increasing the accuracy of PM results in quite a high request in terms of computational requirements (Carchen et al., 2019). This fact limits

their use in the wild where substantial computational capabilities are seldom available (Carchen et al., 2019).

DDMs, instead, do not require any a-priori knowledge of the physical system, but rather are built on historical data collected from the real system. They usually require a large amount of data and a large amount of computational resources to be constructed (i.e., the learning phase) to reach a satisfying performance in terms of model accuracy (Coraddu et al., 2015). Instead, once the model is constructed, its use for making predictions (i.e., the forward phase) is computationally inexpensive (Coraddu et al., 2016) and this has big added value for DDMs as only the forward phase needs to be exploited in order to use them in operation. However, since they rely only on historical observations, DDMs work well in the statistical sense (i.e., on average), but they can produce implausible estimations (i.e., not physically plausible estimations) in particular situations (Coraddu et al., 2021).

HMs have been developed to fill the gaps of PMs and DDMs and develop models able to take the best of the two worlds (Leifsson et al., 2008). HMs, in fact, can be able to: exploit the mechanistic knowledge of the system and avoid implausible predictions, reduce the computational requirements of a PM by exploiting historical data, and reduce DDMs' need for large amounts of historical data by starting from an already good approximation of the phenomenon provided by PMs (Haranen et al., 2016).

Advantages and disadvantages of PMs, DDMs, and HMs for estimating the impact of biofouling on vessel's hull and propeller performance will be discussed in detail in the following sections, presenting and analysing examples of models proposed in the literature belonging to each one of these categories. For each example, the accuracy obtained by the model on real-word or synthetic data has been reported, if available.

4. Analytical review

In this review, PMs, DDMs, and HMs proposed in literature for estimating the impact of biofouling on vessel's hull and propeller performance have been analysed. In particular, among the variety of methods proposed in the literature, the models presented in this work have been chosen to represent all the different approaches to the problem.

The methods presented for each category were selected according to the following criteria: recently developed models (from 2015 to 2021) or models between 2000 and 2015 with at least 25 citations.

In the case of PMs, the most exploited and effective methods for predicting the hull and propeller's deterioration due to fouling are CFD models, which incorporate fouling condition specific roughness properties into the wall function of the CFD software (Song et al., 2019, 2020c,a,b; García et al., 2020; Farkas et al., 2020b,a, 2021b,a). Other
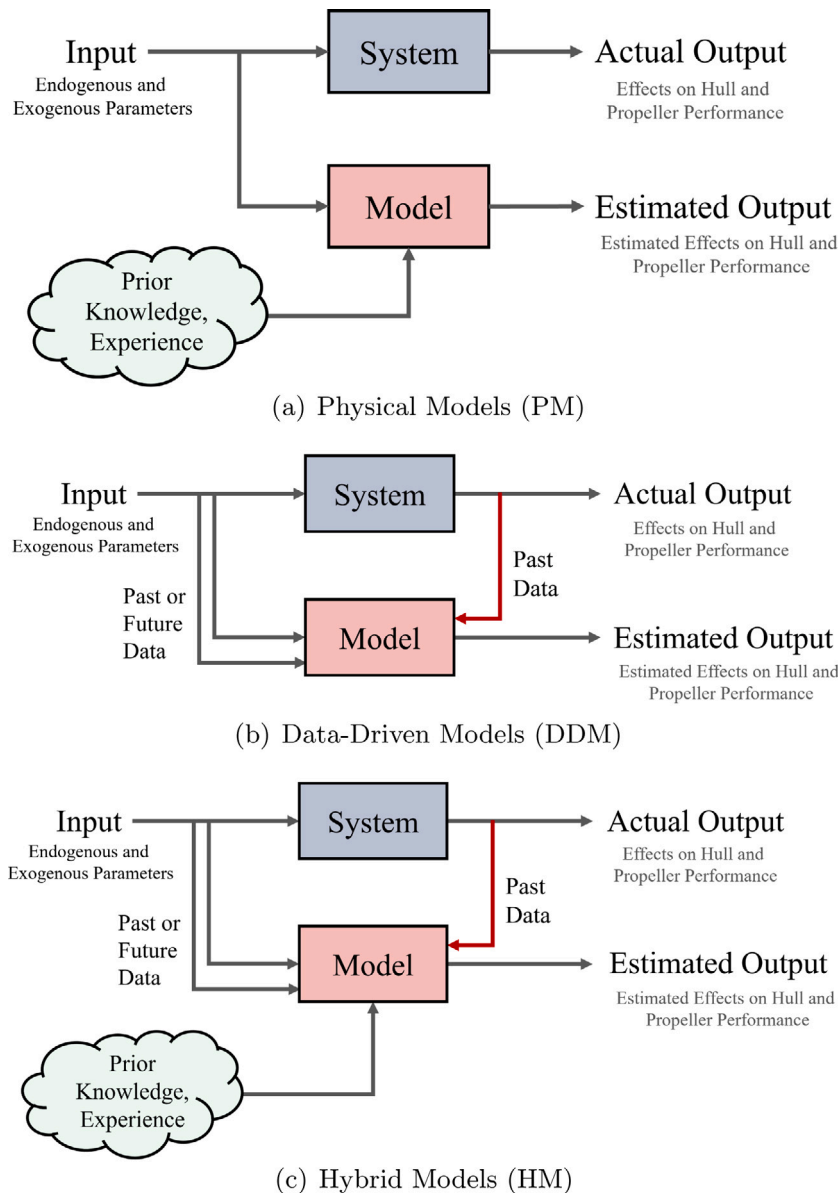
(a) Physical Models (PM)

(b) Data-Driven Models (DDM)

(c) Hybrid Models (HM)

Fig. 4. The three performance modelling approaches.

commonly exploited models are based on Granville's boundary layer similarity law scaling (Schultz, 2007; Schultz et al., 2011; Turan et al., 2016; Demirel et al., 2017, 2019; Uzun et al., 2019), which extrapolate flat plate experimental results into full-scale resistance and powering predictions for vessels.

In the case of DDMs, instead, the most exploited and effective methods for determining biofouling's impact on performance are based on artificial neural networks (Pedersen and Larsen, 2009a; Coraddu et al., 2019b; Senteris et al., 2019; Laurie et al., 2021; Karagiannidis and Themelis, 2021). Additionally, classification methods based on neural networks are used to identify different levels of biofouling (Wang et al., 2006; Bloomfield et al., 2021) and biofouling species (Chin et al., 2017).

For what concerns HMs, this approach has been less investigated in the literature and no methods have so far been proposed for assessing biofouling's impact on the vessel's hull and propeller performances.

In the following sections, advantages and disadvantages of PMs, DDMs, and HMs and relevant examples have been analysed in detail. Moreover, for each class of models, tables have been reported summarising the following aspects (if available):

- Input data: the data that the models require to make the desired estimation;
- Data origin: synthetic data or real-world data collected during sea-trials or operations by on-board sensors or by exogenous sources;
- Amount of data: the amount of data exploited to build and validate the models;
- Method: the technique used by the models to predict the output;
- Output: what parameter(s) the model actually estimates;
- Accuracy: the accuracy obtained by the models;

A section is dedicated to show how, in some cases, PMs have been translated into industry standards (Section 4.1.1). Physical models have been around the longest, therefore they are considered by actors in Maritime to be more robust and trustworthy (Carchen et al., 2019).

4.1. Physical models

PMs are the most well-established numerical approach with regard to assessing the biofouling state (Logan, 2012). PMs, as already

explained before, rely on the a-priori physical knowledge of the phenomenon and are built upon a set of governing laws and assumptions (Carchen et al., 2019). The complexity, the accuracy, and the computational requirements of a PM vary by adding or removing some assumptions (Atlar et al., 2018). To model the hydrodynamic performance of a ship and then quantify the negative impact of the different stages of the biofouling, PMs estimate the total resistance of a vessel or its different components (i.e. wind, waves, currents, and sometimes the rudder effect) through experiment and simulation (Adland et al., 2018). As PMs are the most popular numerical approach, many exist in literature with different levels of complexity.

Among PMs, Experimental Fluid Dynamics (EFD) represents the baseline for biofouling state estimation. EFD consist of conducting experiments in a controlled test environment, such as towing tanks and cavitation tunnels, with the goal of quantifying a target effect on hydrodynamic performance (Carchen et al., 2019). There is a long history of research utilising such techniques, which is well described by Demirel et al. (2017) who utilise a series of towing tests on flat plates using artificial 3D printed barnacles to determine the effects of barnacle height and coverage on vessel resistance and powering. The main drawback of EFD is their high associated costs and the limitation to specific experimental conditions. In fact, it is both time and cost intensive to conduct a rigorous experimental procedure which covers many operational scenarios (Carchen et al., 2019). Moreover, experimental facilities often are not suitable for full-scale testing, limiting EFD to model scale and leading to results often being extrapolated to full-scale for further analysis. For example, for the analysis of biofouling's impact on vessel performance, the Granville's similarity law scaling procedure (Granville, 1958, 1987) is often used to translate laboratory-scale results into a prediction of the impact of fouling. This procedure was first introduced by Schultz (2004, 2007) and it has been employed extensively in research even since (Schultz et al., 2011; Turan et al., 2016; Demirel et al., 2017, 2019; Uzun et al., 2019; Farkas et al., 2020a). Ultimately, EFD is not often used on its own to determine fouling effects, but rather as a source of information employed in more advanced PMs (Uzun et al., 2019; Farkas et al., 2020b; Schultz, 2007; Song et al., 2020c; Demirel et al., 2017; Schultz, 2004; Demirel et al., 2019; Atlar et al., 2018).

Another approach, an alternative to EFD, to determine biofouling's impact on ship performance, involves estimating the total resistance and then correcting for its various components which allows the isolation of fouling's contribution (Adland et al., 2018). This estimation has often been performed with resistance modelling methods (Logan, 2012; Adland et al., 2018), which were originally developed by Todd Todd (1967). A collection of separate empirical and non-empirical methods for each resistance component can be exploited (Logan, 2012; Pedersen and Larsen, 2009a). A good example is the work by Foteinos et al. (2017), where an engine model in the MOTHER software is first calibrated according to shop test and sea trial reports and then used to estimate total ship resistance; empirical formulae are used to determine calm water resistance, air resistance, and wave-added resistance, which are then subtracted from the total ship resistance to obtain the contribution of hull & propeller fouling. Researchers include different levels of detail in their decomposition of total resistance (Logan, 2012). For example, Carchen et al. (2019) developed a real-time biofouling impact monitoring system on the basis of automatic data collection and resistance modelling. The authors considered not only the wind, wave, and calm water resistance (which are usually taken into account Foteinos et al., 2017) but also the steering and shallow water effects. Resistance modelling is based on a-priori physical knowledge and, therefore, results in only physically plausible results. However, these results are often inaccurate, partially due to a need for estimating several unknown friction-related coefficients (Pedersen and Larsen, 2009a).

The state-of-the-art PMs are surely the ones based on CFD, which often replace or supplement EFD and resistance modelling (Carchen

et al., 2019). CFD demonstrate high accuracy using computers to solve complex Navier-Stokes equations describing fluid flow. However, CFD are very computationally expensive when compared to other methods (Karagiannidis and Themelis, 2021). Similar to EFD methods, CFD simulations are confined to the analysis of a single flow or operational condition at a time, which limits their practical real-time applicability (Carchen et al., 2019). Nonetheless, a large body of research relies on CFD to measure biofouling impact (Farkas et al., 2020b, 2021a,b; Song et al., 2020c; Atlar et al., 2018; Farkas et al., 2020a; Song et al., 2020a; García et al., 2020; Song et al., 2019, 2020b). The CFD approach to estimating the biofouling state is to consider increases in the vessel's surface roughness due to specific biofouling conditions and incorporate these in the wall function by means of appropriate roughness functions (Schultz, 2007). The specific roughness functions are usually determined using experimental methods (Schultz, 2004). Additionally, data collected from EFD is used to validate this type of PMs (Song et al., 2019, 2020c,a,b; Farkas et al., 2020b,a, 2021a,b).

PMs are quite useful not only to get an estimation of the biofouling state but also to gain a better understanding of the hydrodynamic behaviour of fouled vessels and surfaces (Carchen and Atlar, 2020). However, even nowadays, there are still specific physical phenomena which cannot be easily modelled through PMs (Montewka et al., 2019). Consequently, in realistic scenarios, PMs often lack in accuracy or are too computationally demanding.

For a more precise view of the current state-of-the-art approaches, Table 4 summarises the most relevant contributions in the field of PMs for biofouling state estimation.

4.1.1. Industry standards

The current industry standard for estimating changes in ship hull and propeller performance consists of applying the ISO 19030 developed by the International Organisation for Standardisation (ISO). The aim of the ISO 19030 is to prescribe practical methods for measuring changes in ship specific hull and propeller performance and to define a set of relevant performance indicators for hull and propeller maintenance, repair, and retrofit activities (ISO, 2016a). The ISO 1903 consists of three parts:

1. an explanation of the general principles that are adopted (ISO, 2016a);
2. a description of the default and most accurate method that can be applied for determining metrics for changes in hull and propeller performance (ISO, 2016b);
3. a set of alternative methods that can be used in case the default procedure cannot be adopted (ISO, 2016c), enhancing the range of applicability of the standard.

ISO 19030 has been identified as a good starting point for vessel owners and operators to track hull and propeller performance, considering the previous lack of an official standard (Koboević et al., 2019). However, it has received criticism for its underlying methods (Bertram, 2017), e.g., the suggested corrections and filtering procedure (Coraddu et al., 2019b; Farkas et al., 2020b) and its performance assessment (Oliveira et al., 2020). In fact, most performance monitoring approaches utilise a reference condition, which is then compared to real-time performance to determine any noticeable shifts (Bertram, 2017). However, these corrections are often done through simplistic methods with narrow ranges of applicability which demonstrate inaccurate results. The ISO 19030 is no different as it requires filtering out of operating points that are outside of the applicability of the methods' assumptions (Coraddu et al., 2019b). While the ISO 19030 standard is considered a positive step forward from previously non-existent official guidance to hull and propeller monitoring, it is still affected by issues which have not yet been resolved (Oliveira et al., 2020).

Table 4

Summary of PMs for monitoring and evaluating the biofouling state and effects on vessels' hull and propeller performance.

Ref.	Method	Input data	Data origin	Amount of data	Output	Accuracy
Schultz (2007), Schultz et al. (2011)	Granville's similarity law analysis based on laboratory-scale experimental results.	Fouling condition and antifouling paint specific roughness functions, vessel geometry & particulars.	Experiment derived roughness functions.	Roughness functions for 7 surface conditions.	Predictions of full-scale ship resistance and powering for a range of fouling conditions and roughness.	Extrapolated full-scale results are compared with trial results for similar hull forms: Reference values of 24% and 8%, compared to extrapolated results of $22 \div 32\%$ and 9%.
Logan (2012)	Propeller power absorption technique which uses the propeller as an instrument to estimate speed or power.	Propeller particulars, ship performance data.	Automated data acquisition systems installed on-board.	After filtering, 3326 entries were used.	Power increase and/or speed loss due to fouling.	Average speed and shaft horsepower absolute errors of 1.8% and 0.9% respectively.
Foteinos et al. (2017)	Shaft torque prediction through an engine simulation software fed with recorded engine data, coupled with resistance modelling	Engine shop test data, sea trial reports, performance reports, noon reports, engine and vessel geometry	Real-world engine & vessel trial and operation.	Four Panamax vessels' operational data.	Estimation of resistance due to fouling through increases in the Propeller Law and Fouling Resistance coefficients.	Results with more than 5% deviation from sea trials were discarded from analysis.
Turan et al. (2016), Demirel et al. (2017)	Granville's similarity law analysis based on a series of flat plate towing tests for different artificial barnacle heights & coverage.	Barnacle size and coverage values.	3-D scans of actual barnacles.	10 different combinations of barnacle size and coverage.	Added resistance diagrams are plotted using predictions of added resistance and the effective power of ships for varying barnacle fouling conditions.	Uncertainties estimated through repeatability tests based on a procedure defined by the ITTC: Friction coefficient uncertainty below 4%; Roughness function uncertainty was mostly under $+/-6\%$, however, for small barnacles it was below 28%.
Demirel et al. (2019)	A prediction code based on Granville's similarity law is used to predict the effects of different fouling states.	Roughness height, roughness functions, corresponding roughness Reynolds numbers and desired ship lengths.	Experiment derived roughness functions from Schultz (2007).	Roughness functions for 7 surface conditions.	Frictional resistance coefficient values which are used to generate added resistance diagrams for the prediction of increases in frictional resistance coefficients and effective powers of ships due to a range of surface conditions.	The authors provide no information on the accuracy of the used method.
Carchen et al. (2019), Carchen and Atlar (2020)	A ship performance monitoring system, based on real-life data collection and resistance modelling.	Time, SoG, Course over Ground, Heading, SoW, Propeller speed, Propeller Torque, Propeller Thrust, Rudder angle, Wind speed, Wind direction, Wave amplitude, Wave spectrum, Wave properties	Automatic on-board monitoring system.	Data from sea trials and normal service with 1 Hz sampling frequency.	Normalised delivered power, apparent wake fraction, effective wake fraction, fouling coefficient and change in frictional resistance coefficient	The authors present no validation study, which would give indication into the accuracy of their method.

Table 4 (*continued*).

Uzun et al. (2019)	A time-dependent biofouling growth model based on field test data coupled with a frictional resistance and powering prediction model based on Granville's similarity law.	Vessel idle times, field test data for AF coatings, water temperature, biofouling condition specific roughness functions & ship particulars.	Static field tests from a paint company.	Test from one to three years in two regions.	Fouling Rating, calcareous fouling surface coverage, percentage increase in frictional resistance & percentage increase of effective power.	Following the validation of their model, the authors conducted a case study in which the model committed a 4% error when estimating the increase of effective power due to fouling.
Song et al. (2019)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of KCS hull.	Experiment derived roughness functions from Demirel et al. (2017).	Roughness functions for 10 fouling conditions.	Fouling effects on the resistance components, form factors, wake fractions and flow characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 1%. As part of a validation study, the modified wall-function results from CFD were compared with experimental results, however, exact values for committed errors are not given.
Song et al. (2020c)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of KCS and KVLCC2 hulls.	Experiment derived roughness functions from Demirel et al. (2017).	Roughness functions for 3 surface conditions.	Fouling effects on the resistance components, form factors, wake fractions and flow characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 1%. Validation study by comparison with experimental results: observed errors are within 5% of reference values.
Song et al. (2020a)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of the KP 505 propeller and the KCS hull.	Experiment derived roughness functions from Demirel et al. (2017).	Roughness functions for 10 surface conditions.	Effects of fouling on full-scale ship resistance and powering, as well as flow characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 0.1%. Validation study by comparison with experimental results: observed errors are within 5.5% of reference values.
Song et al. (2020b)	CFD implementation at full-scale utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, full-scale KP505 propeller geometry and particulars	Experiment derived roughness functions from Demirel et al. (2017).	Roughness functions for 10 surface conditions.	Propeller open water performance (i.e. Thrust coefficient, Torque coefficient and open-water efficiency)	Verification study based on grid convergence index (GCI) method: GCIs under 1%. As part of a validation study, the results from CFD were compared with experimental results, however, exact values for committed errors are not given.

Table 4 (*continued*).

García et al. (2020)	A validated RANS solver (OpenFOAM) utilised according to experimentally investigated surface roughness properties.	Fouling conditions' & hull coatings' specific roughness functions, geometry and particulars of the KCS hull.	Experiment derived roughness functions.	Experiments for 4 marine coatings.	Impact of fouling on ship total resistance and frictional resistance.	Verification study based on grid convergence index (GCI) and correction factor (CF) methods: GCIs and CFs around 10%. Validation study by comparison with synthetic CFD results from Song et al. (2019): average deviation of 5% for drag coefficient and 5% for frictional resistance coefficient.
Farkas et al. (2020b)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of the KP 505 propeller and KCS hull.	Experiment derived roughness functions from Schultz et al. (2015), Farkas et al. (2018).	Roughness functions for 8 surface conditions.	Impact of biofilm on ship propulsion characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 3.5%. Validation study by comparison with experimental results: observed errors are within +/ − 6% of reference values.
Farkas et al. (2020a)	The ITTC 1978 Performance Prediction Method is modified by incorporating Granville's similarity law scaling in combination with CFD.	Roughness functions, vessel geometry and particulars, results from towing tank experiments.	Experiment derived roughness functions from Schultz et al. (2015).	Roughness functions for 8 surface conditions.	Impact of fouling on ship resistance and propulsion characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 4.9%. Validation study by comparison with experimental results: observed errors are within 4.2% of reference values.
Farkas et al. (2021b)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of WB, KP505 & KP458 propellers	Experiment derived roughness functions from Schultz et al. (2015), Schultz (2004).	Roughness functions for 14 surface conditions.	Open water performance (i.e. Thrust coefficient, Torque coefficient and open-water efficiency) of propellers	Verification study based on grid convergence index (GCI) method: GCIs under 5%. Validation study by comparison with experimental results: observed errors are within 2.7%, 2.5%, and 5.4% of reference values for WB, KP505 & KP458 respectively.
Farkas et al. (2021a)	CFD implementation utilising biofouling state specific roughness functions.	Fouling conditions' specific roughness functions, geometry and particulars of KCS, KVLCC2 & BC hulls	Experiment derived roughness functions from Schultz et al. (2015).	Roughness functions for 8 surface conditions.	Impact of fouling on ship resistance and propulsion characteristics.	Verification study based on grid convergence index (GCI) method: GCIs under 4.2%. Validation study by comparison with experimental results: observed errors are within 2.1%, 4.2%, and 2.6% of reference values for KCS, KVLCC2 & BC respectively.

4.2. Data-driven models

In recent years, DDMs have been growing in popularity in the field of ship performance modelling (Montáns et al., 2019). Unlike PMs, they do not require any a-priori knowledge about the underlying physical principles (Coraddu et al., 2019b). In the field of biofouling, DDMs are built by applying predictive ML algorithms on historical data, collected from automatic on-board data logging systems (Coraddu et al., 2019b,a; Laurie et al., 2021), noon reports (Pedersen and Larsen, 2009b; Adland et al., 2018), and vessel inspections and surveys (Bloomfield et al., 2021). Generally, the main limitations of DDMs are the need for high quantity and quality data (Coraddu et al., 2017) and their possible lack of physical meaning (Coraddu et al., 2021). Nevertheless, DDMs can account for many ship-specific and environmental phenomena, that might be difficult, or even impossible, to model with PMs (Coraddu et al., 2019b), with very limited computational overhead.

DDMs have been successful and have increasingly received the attention of researchers and the Maritime industry because modern on-board equipment is capable of recording and storing large amounts of good quality historical data (Laurie et al., 2021). In fact, advanced data logging systems are nowadays a standard in newbuilds, as well as being conveniently installed during the retrofitting of older vessels (Lim et al., 2019). This trend is expected to continue in the future (Rødseth et al., 2016).

Research that exploits DDMs for biofouling state estimation is still in its infancy and a limited number of works are available in the literature. Nonetheless, DDMs have already showed promising results when compared to PMs (Pedersen and Larsen, 2009a,b) and the ISO 19030 standard (Coraddu et al., 2019b).

DDMs, in fact, can also easily leverage on structured information like images and videos (Goodfellow et al., 2016) to better estimate the biofouling state. For example, Wang et al. (2006) were able to accurately classify fouling conditions through image recognition techniques, combined with an Artificial Neural Network. Due to an excellent accuracy, despite using research-tailored input images, they argue that manual underwater surveys could be replaced with artificial methods. Bloomfield et al. (2021), similarly to Wang et al. (2006), leveraged on Convolutional Artificial Neural Networks to classify underwater survey images of a vessel's hull according to a tiered fouling level framework. The achieved accuracy is shown to be very close to expert agreement rates on a subsample of the used image library. Chin et al. (2017) collected an image database containing entries for 10 common fouling species from internet sources and used it in combination with an image processing technique to train a Convolutional Artificial Neural Network. The latter is then used to classify biofouling according to species that are present and fouling density.

Apart from DDMs which leverage on images of the hull, other methods can be used to determine the biofouling state. For example, Coraddu et al. (2019a), utilising just a set of real data collected on-board from a real vessel, developed an unsupervised DDM based on outlier detection ML algorithms to estimate the hull and propeller biofouling condition. Through a rigorous and statistically robust approach, using as little as 10 manually labelled samples, a very high accuracy is achieved. In fact, the research by Coraddu et al. (2019a) demonstrates that DDMs can be effective without using very large historical datasets, which is the common opinion.

Even though having an indication of a vessel's biofouling state is valuable for maintenance-related planning and decision making processes, being able to evaluate the exact impact that biofouling has on performance is surely much more valuable (ISO, 2016a). In this context, DDMs have shown a very high potential and effectiveness in many studies. For example, Coraddu et al. (2019b) proposed DDMs based on deep learning models able to quantify the speed loss due to biofouling in real-time by using just data coming from the vessel's on-board monitoring systems. The developed DDMs show to outperform the state-of-the-art ISO 19030 industry standard, providing more reliable and actionable

results. Other DDMs have also been developed to determine speed loss due to biofouling (Erol et al., 2020).

Apart from using a speed loss prediction as proxy for the biofouling state estimation, the most popular performance metric in terms of quantifying biofouling is shaft power (Pedersen and Larsen, 2009a,b; Senteris et al., 2019; Laurie et al., 2021; Karagiannidis and Themelis, 2021). Recently, Laurie et al. (2021) employed and compared a set of ML techniques (i.e., linear regression, decision tree, k-nearest neighbours, artificial neural networks, and random forest) when predicting the shaft power of a fouled vessel. Considering the complex nature of biofouling phenomena, a very high prediction accuracy (errors below 2%) was observed for some of the statistical methods. In fact, DDMs can accurately estimate vessel performance in a broad range of operating conditions because they are built on historical data, as opposed to the majority of PMs.

Another aspect that needs to be carefully taken into account when estimating the biofouling state is the impact of hull and propellers cleaning. For example, Adland et al. (2018) investigated the impact of hull and propeller cleaning on vessel performance. In particular, they proposed a DDM capable of determining the performance impact of the underwater cleaning and the dry-docking of a vessel. To asses the validity of the proposal, the authors rely on a dataset of daily noon reports combined with a historical log of cleaning instances.

For a more precise view of the current state-of-the-art approaches, Table 5 summarises the most relevant contributions in the field of DDMs for biofouling state estimation.

4.3. Hybrid models

HMs are a hybridisation between PMs and DDMs. In a HM, the PM and the DDM are combined to build a model which uses both a-priori physical information for the underlying phenomenon as well as historical data (Carchen et al., 2019). For example, the prediction of a PM can be used as an initial estimate to feed into a DDM (Coraddu et al., 2021). HMs aim to address the main setbacks of PMs (i.e., computational requirements and accuracy) and DDMs (i.e., possible lack of a physical interpretation and need for large amount of data).

By looking at the literature, no applications of HMs to biofouling have yet been proposed and this represents a clear research gap. In fact, there is an opportunity to utilise the large amount of high-quality PMs in literature to supplement DDMs. A simple combination of state-of-the-art approaches may result in an HM able to outperform the original model in terms of accuracy, computational complexity, data requirements, and physical interpretability. In fact, HMs have shown their potential within other niches of vessel performance modelling with favourable results (Haranen et al., 2016): Leifsson et al. (2008) successfully utilised a HM, which outperformed both a PM and a DDM, for predicting vessel speed and fuel consumption in the scope of vessel operational optimisation; Similarly, Coraddu et al. (2015) compare the performance of PMs, DDMs and HMs in predicting the fuel consumption of a vessel in a real scenario and conclude that HMs improve upon the accuracy of PMs and the data requirements of DDMs; Additionally, in Coraddu et al. (2017), Coraddu et al. utilise the latter to effectively optimise vessel trim in real operational conditions; Swider et al. (2017) look into the complementarity potential between PMs and DDMs and reach encouraging conclusions, which are supplemented by an example application of an HM for predicting the speed/power of an offshore vessel; Coraddu et al. (2018) utilise a HM to accurately predict engine temperatures during operational dynamic manoeuvring based on engine models and engine measurements for a Holland class patrol vessel and show that, for this, a hybrid approach greatly outperforms a DDM; Yang et al. (2019) use real operational data from a crude oil tanker over a 7-year sailing period to demonstrate the accuracy and reliability of a genetic algorithm-based HM in predicting vessel fuel consumption; Montewka et al. (2019) successfully incorporate the use of a HM for evaluating ship performance in ice-covered water in a

Table 5

Summary of DDMs for monitoring and evaluating the biofouling state and effects on vessels' hull and propeller performance.

Ref.	Method	Input data	Data origin	Amount of data	Output	Accuracy
Chin et al. (2017)	Convolutional Neural Network paired with OpenCV image processing.	A database of images of different fouling organisms and fouling density.	Internet.	1825 images of 10 common fouling species.	Classification of the fouling species and density of fouling.	Mean classification accuracy of 74.75% & standard deviation of 7.92%. No model accuracy is provided for determining fouling density.
Coraddu et al. (2019a)	One-Class Support Vector Machines and Global k-Nearest Neighbour methods for outlier detection.	A featureset, comprised of measured values from the ship monitoring systems and wave buoy data.	On-board monitoring systems & wave buoys.	39(+10) features, unspecified number of samples.	Hull and propeller fouling is identified and labelled.	Even with as little as 10 labelled samples, the proposed model has impressive accuracy when classifying whether the ship is fouled, achieving 0.04+/−0.001 Average Misclassification Rate.
Bloomfield et al. (2021)	Convolutional Neural Network.	A dataset of underwater images of ship hulls, labelled according to their Simplified Level of Fouling (SLoF).	In-water surveys of around 300 vessels.	10263 images with SLoF labels.	Estimates for SLoF, based on input image.	Mean average precision of 0.796, standard deviation of 0.023.
Adland et al. (2018)	Before–after and difference-in-differences estimators.	A dataset, consisting of daily vessel parameter measurements, combined with a historical log of hull & propeller cleanings.	Daily noon reports & maintenance logs.	7868 daily observations after data cleaning & 28 maintenance activities.	Impact of hull & propeller cleaning activities on the average fuel consumption of examined vessels.	The proposed procedure is applied at an arbitrary point in time, instead of the time of a known cleaning for validation. This is repeated 1000 times and the results indicate an encouraging 0.002%+/−0.086% average change in fuel consumption at these arbitrary points.
Pedersen and Larsen (2009a)	Artificial Neural Network.	A dataset, comprised of measured values from the ship monitoring system.	On-board monitoring.	4 8-feature datasets, consisting of a total 679 10-minute averages.	A 10-minute average propulsion power estimate.	A 2.7% cross-validation error is reported, however, there is no indication of its interval of confidence. Also, there is no unbiased test of the model where a set of data, omitted in training and validation, is used.
Coraddu et al. (2019b)	Deep Extreme Learning Machine.	A dataset, comprised of measured parameters from the ship's monitoring system, combined with a historical log of hull & propeller cleanings.	Data logging systems & maintenance logs of two Handymax tankers.	15 min averages over nearly 5 years for 17 features & 9 cleaning events.	Speed through Water & speed loss percentage, as well as estimates for timing of maintenance activities	The proposed method shows a higher level of reliability when compared to the state-of-the-art ISO 19030 industrial standard. Additionally, all changes, corresponding to a cleaning event, are detectable. No indication of accuracy of the DELM when predicting Speed through Water.
Senteris et al. (2019)	Artificial Neural Network	A featureset, comprised of measured parameters from a ship's monitoring system, as well as environmental features.	VLCC automatic monitoring system.	11 features, unspecified number of samples.	Shaft power estimate.	Graphs on the error distribution are provided, however, authors provide no indication on which the final selected model is and its exact accuracy.

Table 5 (*continued*).

Erol et al. (2020)	Curve fitting and Detrended Fluctuation Analysis (DFA)	Two datasets, collected 9 months apart, that include ship speed, propulsion power, fuel consumption, generated power, battery power, aft & fore draught.	Alarm monitoring system of an electric ferry.	A week of data at the start & one after 9 months (1 sample per minute).	Speed loss estimate after 9 months of operation.	Only Motor power vs Vessel speed curve fitting accuracy is provided: best fit R-square & RMSE - 0.9999 & 0.07248 before and 0.9999 & 0.05637 after 9 months.
Laurie et al. (2021)	Multiple Linear Regression, Decision Tree (AdaBoost), KNN, ANN and Random Forest.	A dataset from a ship's monitoring system, expanded through artificial feature generation and additional wave information.	On-board automatic ship monitoring & CMEMS.	20 features with 10571 entries after cleaning.	Shaft power.	MAPEs & RMSPE: Multiple Linear Regression - 6.453% 0.0930%, Decision Tree - 6.987% 0.0932%, KNN - 1.245% 0.0302%, ANN - 1.893% 0.0317% and Random Forest - 1.171% 0.0264%.
Karagiannidis and Themelis (2021)	Artificial Neural Network	A dataset from a ship's monitoring system, expanded through artificial feature generation.	Container ship continuous monitoring system.	14 (+5) features - 1 min samples over 19 months.	Main Engine Fuel Oil Consumption (t/24hr) or Shaft Power (kW) estimate.	RMSE & R-square for Fuel Consumption - 0.78 & 0.998 with and 0.96 & 0.997 without fouling feature. RMSE & R-square for Shaft Power - 132.07 & 0.999 with and 203.19 & 0.997 without fouling feature.

route planning methodology for an ice going bulk carrier; Liu et al. (2020) build a digital twin based on a HM which provides a satisfying prediction of ship speed and fuel consumption and demonstrate the application effects of the HM through an arrival time forecast and a weather routing showcase; Finally, Coraddu et al. (2021) combine PMs and DDMs to build a fast, accurate and physically grounded model that can be used for real-time prediction of engine performance parameters in dynamic conditions in order to identify emerging failure early on and establish trends in performance reduction.

5. Open problems and future perspectives

After providing a complete review of the numerical methods for monitoring and evaluating the biofouling state and effects on vessels' hull and propeller performance in Section 4, the current section summarises the open problems and future perspectives of this field of research.

For what concerns the open problems, there are at least two main aspects that are worth discussing. Firstly, regardless of the numerical methods adopted, filtering out unfavourable exogenous factors which might alter the biofouling state estimation and the effect of the environmental conditions is of great importance. In this respect, robust filtering and outlier detection procedures should be carried out to feed the PMs, DDMs, or HMs with reliable data. Secondly, some of the proposed approaches are computationally expensive which might prevent their use in real-time for maintenance-related decision making processes. Although DDMs can be considered computationally inexpensive in the forward phase, the training phase (to build or update the model) can be quite taxing (especially if this phase is performed on-board). Moreover, the additional burden of detecting and filtering outliers has to be accounted for real-time applications. For this reason, researchers should focus their attention on the development of numerical frameworks which also take into account computational burden.

Focusing our attention on the future, the authors foresee a wider use of hybridisation techniques for biofouling assessment. As reported in Section 4.3, to the best of the author's knowledge, no applications of HMs to biofouling have yet been proposed. Leveraging on state-of-the-art PMs, in the upcoming years, researchers have the unique opportunity to exploit the on-board operational data to develop HMs for a more accurate, reliable, computationally inexpensive, and physically grounded biofouling state assessment. In fact, HMs have the potential to offer the accuracy, speed, and flexibility of data-driven approaches, while maintaining some physical knowledge of the problem through simplistic PMs, making them an ideal candidate for supporting real-world maintenance strategies. For this reason, the development of HMs could unlock the continuous real-time evaluation of the hull and propeller status, enabling shipowners and operators to select the optimal trade-off between cleaning costs and increased fuel consumption due to biofouling. While adopting HMs for biofouling state and effects estimation is surely a new field for future research, there is still space for improvement for the current approaches. For example, the effects of exogenous factors are not accurately represented by PMs, but rather simple filtering procedures for unmodeled conditions are exploited. DDMs, by construction, can handle this condition by simply considering these exogenous factors in the data collection, nevertheless this requires a large amount of historical data to sample all conditions that the model needs to learn. For this reason, the development and implementation of increasingly advanced data logging and storing systems over the entire global fleet (newbuilds and retro-fittings) is becoming essential. Finally, given the relevance of the topic and its impact on the global shipping footprint, there is a need for an update of the current industry standard to reflect the state-of-the-art in monitoring capabilities providing enhanced and certified numerical procedures for biofouling state assessment.

6. Conclusion

The scope of this work was to review the numerical methods for monitoring and evaluating the biofouling state and effects on vessels' hull and propeller performance. For this reason, the problem of biofouling was first described, its impact on performance, which is summarised in Table 1, and gave insight into the preliminary steps in biofouling related performance modelling such as data acquisition, ideal parameter requirements, listed in Table 2, and desired outputs for impact estimation, summarised in Table 3. The above was then followed by a critical review of approaches to biofouling state and effects estimation. In particular, these were grouped into three families of numerical methods, i.e., PMs, DDMs, and HMs, and analysed them from a practical real-world view point. For each family, strengths and weaknesses were discussed, as well as reviewed the most important approaches that exist in literature and listed these approaches in Table 4 for PMs and Table 5 for DDMs. In short, PMs are based fully on the physical knowledge of the phenomena (providing also the ground for the current industrial standards); DDMs fully rely on historical data to learn the desired model; while HMs are able to exploit both sources of information. Summary tables were created as an additional supplement to the review. Finally, the current open problems and future direction of this important field of research were expanded on.

In summary, PMs have, so far, been the standard approach to biofouling analysis and can achieve good prediction accuracy, however, this is achieved at the expense of an increased requirement for computational resources that prevent their use in real-time applications. DDMs, instead, have the advantage of providing a more accurate near real-time prediction at the cost of a computational expensive training phase. Unfortunately, DDMs can, in some cases, provide results that are not physically plausible due to their statistical nature, however, they have been observed to work well on average For this reason, HMs, which are able to take the best from PMs and DDMs, can potentially offer the optimum solution as they are able to deliver physically plausible results in near real-time. Nevertheless, at the time of writing, HMs have not yet been employed or sufficiently investigated for the specific application of biofouling state and effect estimation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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