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Review

A review on ship motions and quiescent periods prediction models

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ABSTRACT

The prediction of ship motions and quiescent periods, is of paramount importance for the maritime industry. The capability to predict these events sufficiently in advance has the potential to improve the safety and efficiency of several marine operations, such as landing and take-off on aircraft carriers, transfer of cargo, and mating operations between ships. Several models have been proposed in the literature for the prediction of ship motions and quiescent period. This work will review them by first grouping them into three main categories (i.e., physical, data-driven, and hybrid models) and then by detailing the most recent and relevant ones describing the advantages and disadvantages of each approach. Review concludes with the open problems and future perspectives of this important field of research.

1. Introduction

There are several ship operations critical in terms of safety and efficiency which are affected by ship motion (SM): landing and take-off on aircraft carriers, transfer of cargo and "mating" operations between ships, docking manoeuvres, drilling for oil and gas operations, embarkation and disembarkation of cruise passengers between the terminal and the ship, and missile launch (Baitis, 1975; Cox and Long, 2004). In general, SMs are defined by six Degrees of Freedom (6DoF). These 6DoF are divided into two categories taking into account three translational degrees (surge, sway, and heave) and three rotational degrees (roll, pitch, and yaw) along the longitudinal (surge and roll), transversal (sway and pitch), and vertical (heave and yaw) axes, experienced by a ship in time. Based on the application, some motions are more critical than others (e.g., in aircraft landing the vertical motion is surely the most critical one, together with the vertical acceleration respect to the landing position, both determined by a combination of heave, roll, and pitch). The SMs, especially in high sea states and in the presence of strong winds, limit the operational capability of the ship (Zheleznyakova, 2020; Graham, 1990). In fact, SMs are influenced by both endogenous and exogenous factors. Endogenous factors are hull shape and ship weight distribution, action of the propulsion system and stabilisers (in cruising condition) and actions of the dynamic positioning system (at zero/low speed) (Kalikatzarakis et al., 2020; Sørensen, 2011). Exogenous factors, instead, are wind, waves, and currents forces applied to body hull (Benetazzo et al., 2015; Rawson and Tupper, 2001). Therefore, the more adverse the weather conditions are, the more significant the induced SM is, and consequently the risk of keeping the vessel in operations. For example, in high sea states, the landing of an aircraft in carriers or of an helicopter in a destroyer could be quite dangerous (Liu et al., 2017). This operation, in fact, usually relies on the prior experience and the intuition of the pilots of the aircraft to predict and compensate for the relative motion between the ship and the aircraft. Therefore, in severe weather conditions, there is a high risk for the operators to make mistakes and to unsuccessfully conclude the operation: the mission could be cancelled and re-planned to avoid possible accidents, and so injuries to people or damages to equipment (Sherman, 2007; Coraddu et al., 2020). Side by side cargo transfer is another example of marine application critically influenced by the SM. For example, a crane may off-load some dangerous ammunition from a big ship to a small one and consequently the operation can become dangerous in adverse sea states (Küchler et al., 2011; Henry et al., 2001). Another interesting example is the mating operation between a large transport ship and some small ships. The large ship is floating far from shore and the small ships go back and forth between the main ship and the shore. During adverse weather conditions, it may be difficult for the small ships to enter in the large one (Zhao et al., 2004). Also efficiency of ships' docking manoeuvres is affected by SMs: on the path towards the dock, the vessel operator must tackle

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challenges such as passing nearby vessels and compensating for forces induced on the vessel by environmental disturbances. There is a risk to collide with the dock or other vessels if the operation is not carried out correctly, causing expensive damages (Skulstad et al., 2021; Perez, 2005).

In all the above-mentioned applications, the availability of SM prediction systems able to efficiently and effectively predict in advance the SMs while performing the operation would be of paramount importance. In fact, it would allow to empower or substitute the operators intuition and experience with systems able to autonomously and safely conduct these critical operations. For example, in the case of aircraft landing, providing the operator with SM predictions can help him to plan an optimal descent trajectory for safe landing (Yang et al., 2008; Ferrier et al., 2009). In the case of cargo transfer, SM predictions may allow operators to plan the transfer during the time intervals in which SMs are sufficiently small to complete the activity safely and prevent crash of cargo that may even explode in case of ammunition. It is also useful to have predictions for heave compensation to keep the crane motionless with regard to the seabed (Küchler et al., 2011; Ventikos and Stavrou, 2013). Moreover, a smooth mating between ships can benefit from predictions of SMs to correctly time the operation and increase its efficiency. Furthermore, for dynamic positioning systems, the availability of SM predictions may improve their effectiveness (Kalikatzarakis et al., 2020). In many of these examples, the quantity of interest to predict is not the actual SMs, but the time interval during which the SMs are below a certain threshold. That is called, in sea-keeping terminology, Quiescent Period (QP) prediction (Giron-Sierra and Esteban, 2010; Ferrier et al., 2013; Riola et al., 2011). Efficiently and effectively predicting, enough in advance, the QP allows to identify the best time windows in which maritime operations can be safely executed and to set up the tactical planning of such operations. Therefore, there has been a rapidly growing interest in the ability to predict and exploit the QP (Anguita et al., 2002; Riola et al., 2011; Al-Ani et al., 2019). In other cases, such as the stabilisation of the crane on a cargo ship or docking manoeuvres of vessels, the quantity we are interested in estimating is the SMs. Knowing in advance the QP is not enough for this kind of operations, it is necessary to know the exact value of the amplitude and phase of future SMs. In fact, to counteract the vertical motion of the crane in cargo vessels, or in general of the drilling machinery in oil and gas extracting operations, it is necessary to know the exact value of heave to compensate (Chu et al., 2020; Cheng et al., 2019). In the same way, for ships' docking, the predictions of SMs can be used as inputs for on-board systems to adjust speed, direction or engine's parameters according to the predicted value (Koskinen, 2013; Shuai et al., 2019).

QP prediction problem is obviously simpler than SM prediction one. QP prediction, in fact, can be easily retrieved from an accurate SM prediction but not vice-versa. Nevertheless, in literature, the common approach is to first predict the SMs and then identify the QPs since the SM prediction can be used also for other purposes, besides the QPs identification (Carico and Ferrier, 2006; Abujoub, 2019). For example, SM prediction can be also used as input of the on board navigation systems or dynamic positioning systems. However, the problem of modelling the behaviour of a ship in the open sea is a very complex task since, as stated above, endogenous and exogenous factors need to be accounted and modelled. Despite its complexity, the task of reliably modelling the interaction between waves and ship in real-time is of undoubted scientific interest since, as already discussed, there are a lot of applications which benefit from SM predictions. Consequently, many models have been developed during years, such as (Skjetne et al., 2004; Li et al., 2016; Perera and Soares, 2010; Xu et al., 2011; Yin et al., 2013; Abramowski, 2005).

This article is meant to be a review of SM and QP prediction techniques. Other reviews are available on this topic (e.g., Giron-Sierra and Esteban, 2010; Riola et al., 2011) which include a large bibliography of SM and QP prediction methods. Nevertheless, these reviews mostly focus on particular applications (e.g., helicopter landing/take-off operations) or on the effect of different type of input data on the prediction capabilities (e.g., the availability of wave motion predictions). In particular, both Giron-Sierra and Esteban (2010) and Riola et al. (2011) focus on helicopter landing/take-off operations and make a comparison between looking backward methods (which use past motion data as input) and looking forward methods (which use predictions of the wave motion as input) and analyse how the different inputs affect the reachable prediction horizon.

This review, instead, collects SM and QP prediction methods independently from the specific ship operation they have been proposed for. In fact, in this work there are solutions studied, for example, to assist navigation, ship's docking, and helicopter landing. Moreover, this work classifies the collected models in three categories, according to the amount of a-priory knowledge of the problem they have and, for each approach, describes advantages and disadvantages. The three different categories of models are: physical (PM), data-driven (DDM), and hybrid (HM) models. PM require a deep knowledge of the physical phenomena since they use as predictor a physical model of the reality (Naaijen et al., 2009; Graham, 1990). The higher is the detail in the modelling the equations which describe the physical phenomena, the higher is the expected accuracy of the results and the computational time required for the simulation. The second approach, instead, infers the desired model directly from historical data collected by on board machinery and requires no need of any a-priory knowledge of the underlying physical phenomena (Anguita et al., 2002; Deng et al., 2020). However, since these models are not supported by any physical interpretation, they need a significant amount of data to be built. The third approach is a combination of the previous ones and it is based on the integration of a PM and DDM into a single model. The DDM model compensate the secondary effects not modelled by the PM and the PM helps the DDM in reducing the amount of historical data required to train it (Skulstad et al., 2021).

The remaining part of the document is organised as follows: Section 2 contains an introduction to SMs and QPs, an overview of PMs, DDMs, and HMs, and a definition of the metrics used in the analysed articles; Section 3 contains a paragraph for each modelling approach, describing pros and cons and analysing examples of the relevant model taken from the literature; Section 4 summarises the open problems and future perspectives of Artificial Intelligence (AI) in the context of SMs and QPs; Section 5 resumes the results withdrawn from the analysis the state-of-the-art models for SM and QP prediction.

2. Preliminaries

As represented in Fig. 1, a ship at sea is subjected to six types of motions due to wave action: heave, sway, surge, roll, pitch, and yaw. The first three are linear motions. Heaving is the linear motion along the vertical z-axis, swaying is the motion along the transverse y-axis, and surging is the motion along the longitudinal x-axis. The last three, instead, are rotational motions. Rolling is a rotation around a longitudinal axis, pitching is a rotation around the transverse axis and yawing is a rotation around the vertical axis (Thu et al., 2015).

These SMs are caused by exogenous and endogenous factors. Exogenous factors are wind, waves, and currents forces. Endogenous factors are the hull shape and ship's weight distribution (constant factor), actions of the propulsion system and stabilisers, and actions of the dynamic positioning systems (time-variant) (Benetazzo et al., 2015; Rawson and Tupper, 2001). The ship itself, oscillating, generates waves counteracting the wave forces, since energy will be radiated from the ship (the ship acts as a low-pass filter) and this further influences SMs (K. et al., 2008). According to the application and the ship's attitude, SMs can be much influenced by a factor or another one. For example, in cruising condition, the main endogenous factor acting on SMs is the action of propulsion system and stabilisers, while at zero/low speed is the action of the on board dynamic positioning

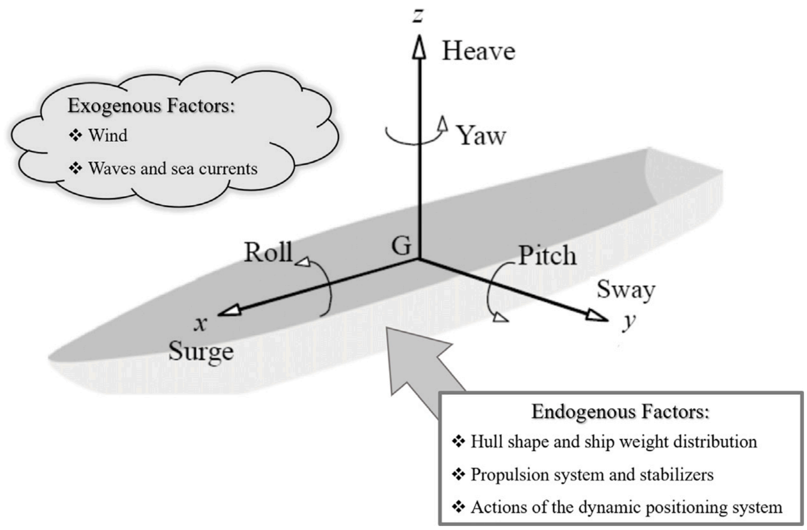


Fig. 1. Ship six degrees of motion.

system to contribute to SM (Cheng et al., 2017; Kalikatzarakis et al., 2020). For what concerns the exogenous factors, for operations at open sea, such as mating operations and cargo transfer, the waves are the most important exogenous factor influencing the SM and, secondly, the wind. In fact, the ship's response characterising these operations is given by motions with zero mean and typical frequencies of the waves (i.e., first order motions) such as in mating operations, or motions with no-zero mean and slower oscillations (i.e., second order motions) such ad cargo transfer and dynamical positioning. Both first and second order motions are induced by waves (Vugts, 1971). For docking operations (Skulstad et al., 2021) and in general operations performed in restricted water, instead, the main exogenous factors are wind, sea currents, and the interaction with other ships or the dock. The waves contribution, instead, is negligible. According to the application, not only the exogenous and endogenous factors influencing the SM change, but also the predominant motions which characterise the ship's response. In fact, according to the application, some SMs are prevalent and more critical and other motions can be neglected. For example, in aircraft landing (Yang et al., 2008; Anguita et al., 2002), the vertical motion and the vertical acceleration of the ship are critical quantities, both determined by a combination of heave, roll and pitch.

The SM may limit the operational capability of the ship, such as the aircraft landing or the cargo transfer which can be performed just at intervals of time where SMs are within acceptable limits, to safely perform the desired activity (i.e., during QP Giron-Sierra and Esteban, 2010; Colwell, 2002), as represented in Fig. 2. Specifications concerning the definition of these limits come from the experience of the operators, or from the literature and the standards. For example, for the problem of helicopter landing on ships, which is one of the most sensitive ship operations, a large amount of literature and standards are available. According to STANAG 4154 (Eriksen et al., 2000), the limits of SMs for take-off and landing operations are a roll of 2.5°, a pitch of 1.5° and a vertical velocity (heave) of 1.0 m/s (all of them given in terms of root mean square amplitude, the other SMs are ignored since they not significantly influence this operation). Besides being characterised by limited SMs, the time interval, to be defined as QP, has to be long enough for operational purposes (i.e., to safely execute and conclude the operation). Moreover, in order to be exploitable in practice, the QP prediction shall be preformed sufficiently in advance to allow the planning and preparation of the desired operation. As far as the QP duration, for helicopter landing, authors of Colwell (2004) state that a QP of 4 s is not enough and 6 s are necessary. Years before, authors of Kolway and Coumatos (1975) stated that it is possible to land with a QP from 6 to 10 s. For what concerns instead the prediction horizon, authors of Baitis (1975, 1977), referring again to helicopter landing and take-off operation, recommend to predict QPs from 8 to 10 s in advance for pitch, and 20 s in advance for roll. Authors of Riola et al. (2011), instead, identifies the following three ranges of forecast time requirements:

- Up to 30 s — fixed wing aircraft (landing on aircraft carrier), helicopter (sling, Vertical replenishment (VERTREP) landing/take off or pickup/delivery);
- Around 1 min — firing operation, general maintenance and repairing activities, launch/recovery of small manned crafts, launch/recovery of unmanned aerial vehicle (UAVs);
- Largely above 1 min — launch/recovery of towed sonar, embarking/disembarking of amphibious vehicles.

Prediction of SM and QP is the subject of this review, which collects predictive models of these quantities.

Modelling the relation between ship's exogenous and endogenous solicitations and the resulting SMs is a special case of inference. Inference is the process of deriving logical conclusions from premises known or assumed to be true (MacKay, 2003). Two main inference methods are exploited in SM and QP prediction: deduction and induction. Deduction starts from a-priory knowledge of the system and deduce (e.g., with approximations) the behaviour of a system in a particular condition. Induction, instead, starts from the observation of the system to induce (e.g., with statistics) a model of the system itself. Fig. 3 reports a graphical representation of the deduction and the induction processes.

In order to forecast SMs and QPs, the model can be inferred using both the physical knowledge of the problem (Connell et al., 2015), the measured time series of the endogenous and exogenous factors influencing SMs and historical SMs data (Peña et al., 2011; Wang et al., 2017). Time series of exogenous factors can be composed of both measurements of current and past values of wind, wave, and sea currents, and future values predicted by on-board systems. Time series of endogenous factors are composed by current and past values of ship's attitude measured by on board sensors or are time-constant variables, such as hull shape and ship's weight distribution. Exogenous data and history of SMs are measured by on board sensors, usually by X-band radar, wind and weather sensors, and the inertial navigation system (Christ and Wernli, 2013). Wave predictions, instead, can be retrieved by processing the X-band radar images (Reichert et al., 2009). All these data are not always available. Predictive methods which process the history of SMs provide accurate predictions, but relevant prediction horizons are very limited, within 10÷15 s (Zhao et al., 2004; Liu et al., 2019). Instead, methods based on actual and predicted wave excitation data

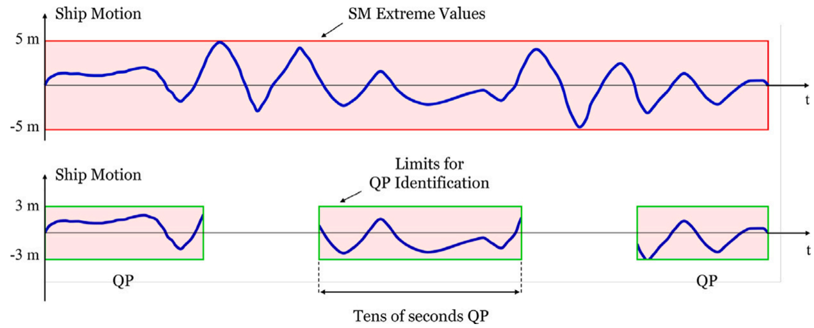


Fig. 2. SMs and QPs.

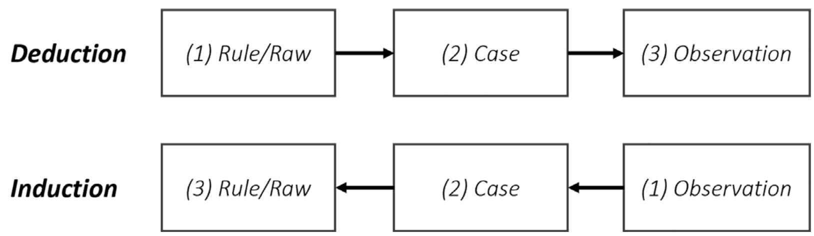


Fig. 3. Inference: deduction and induction.

reach prediction horizons of the order of the minute (Dannenberg et al., 2009; Connell et al., 2015). According to what type of information is used to formulate the model, physical knowledge of the problem and/or measured time series of endogenous and exogenous factors, and SMs data, the construction of the model changes. In particular, three different types of modelling approaches can be identified: PM, DDM, and HM. PMs are built based on a-priory, mechanistic knowledge of the real system (i.e., the numerical description of body hull, propulsion systems, wind and waves forces, and sea currents effects) (Sato et al., 2007; Feng et al., 2013). DDMs, instead, are built based on historical collections of observations (data) of inputs and outputs of the system constituted by a ship floating on the sea surface (i.e., past and/or future wind, waves, sea currents data, and past SMs are the inputs of this system and future SMs are the outputs), exploiting state-of-the-art Machine Learning (ML) techniques (Wang et al., 2017; Kawan et al., 2017). In the case of HM, the PM and the DDM are combined to build models which use both a-priory physical information of the underlying phenomenon and the historical data (Del Águila Ferrandis et al., 2021). Fig. 4 reports a graphical representation of SM and QP models 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 (Howison, 2005; Lewis, 1988). However, usually, increasing the accuracy of PM results in a quite high request in terms of computational requirements (Lavrov et al., 2017). This fact prevent their use for real-time predictions, which is crucial for SM and QP prediction.

DDMs, instead, does not require any a-priory knowledge of the physical system, but they are built on the historical collections of inputs and outputs observations of the real system (data). DDMs usually require a large amount of historical data and a large amount of computational resources to be constructed (i.e., the learning phase) to reach satisfying performances in terms of model accuracy (Kawan et al., 2017). Instead, once the model is constructed, its use for making prediction (i.e., the forward phase) is computationally inexpensive (Vapnik, 1998). However, since they rely only onto the historical observation, these models work well in the statistical sense (i.e., on average), but they could produce implausible predictions (i.e., prediction not physically plausible) in particular situations (Alber et al., 2019).

HMs have been developed to fill the gaps of PMs and DDMs and develop models able to take the best of the two worlds (Del Águila Ferrandis et al., 2021; Coraddu et al., 2017). HM, in fact can be able to: exploit the mechanistic knowledge of the system and avoid implausible predictions, reduce the computational requirements of the PM exploiting the historical data, and reduce the need of large amount of historical data of DDMs, starting from an already good approximation of the phenomenon provided by the PMs (Al-Ani et al., 2019; Skulstad et al., 2021).

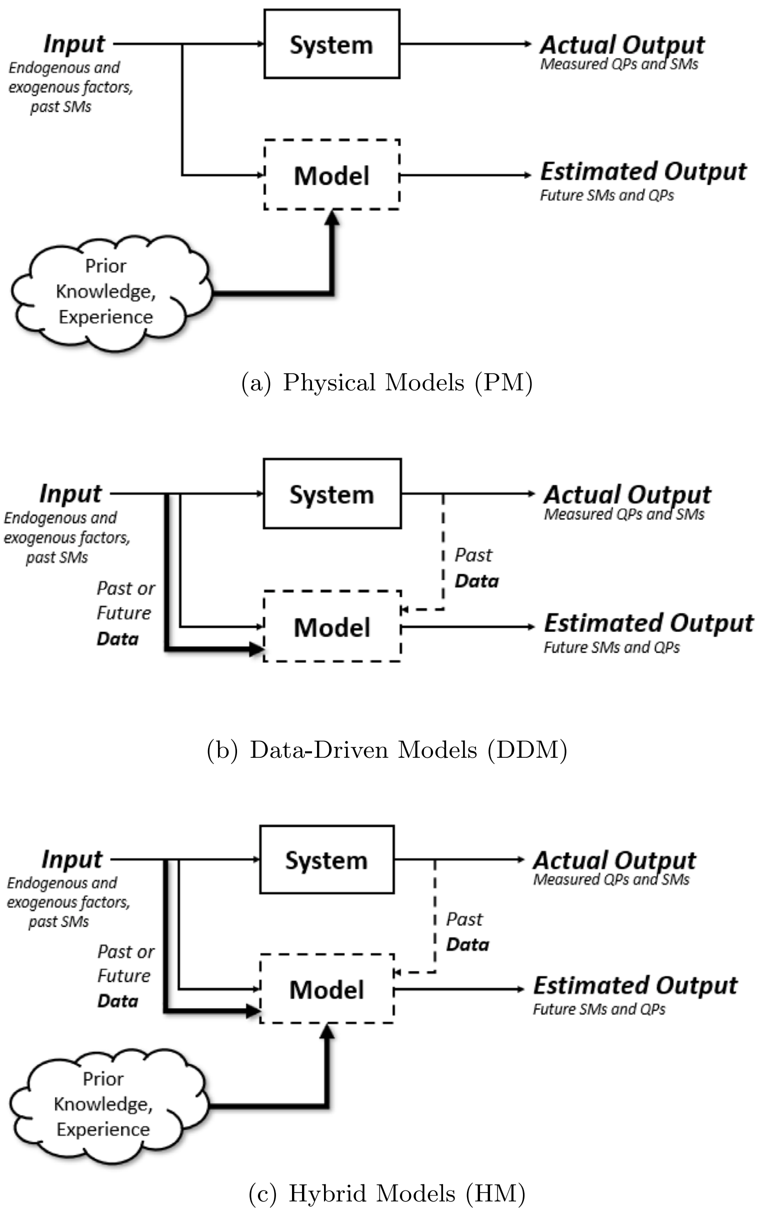
Advantages and disadvantages of PMs, DDMs, and HMs for SM and QP prediction will be discussed in detail in the following sections, presenting and analysing examples of models proposed in the literature belonging to each one of these categories. For each example, the accuracy of the model obtained by the model on real-word data or on synthetic data has been reported. The metrics, used in the cited examples, for model's evaluation are (Coraddu et al., 2017; Zheleznyakova, 2020):

- RAOs (Response Amplitude Operator) comparison (i.e., a kind of transfer function between the incident wave and the motion responses);
- Correlation, R, between predicted and true SM;
- Mean Square Error (MSE);
- Root Mean Squared Error (RMSE);
- Relative Square Error(RSE);
- Mean Absolute Error(MAE).

3. Ship motion and quiescent period prediction

In this review, PMs, DDMs, and HMs proposed in literature for the prediction of SM and QP 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.

In the case of the PM, the most exploited and effective methods for SM and QP predictions are the Linear Potential Flow Models (PL) (Naaijen et al., 2016a; Dannenberg et al., 2009; Connell et al., 2015; Feng et al., 2013), which, even if they make strong assumptions (i.e., wave motions can be decomposed into independent sinusoidal components and the ship is a linear filter), well represent the ship's response in the majority of the cases and are able to give near real-time predictions.



(a) Physical Models (PM)

(b) Data-Driven Models (DDM)

(c) Hybrid Models (HM)

Fig. 4. Models for SM and QP prediction.

Other exploited models, much for predictions of sea-keeping performances than for QP prediction, are Non-Linear Potential Flow models (PNL) (Mortola et al., 2011) and computational fluid dynamics (CFD) techniques (where software tools are used to perform the calculations required to simulate the flow of the ocean surface) (Sato et al., 2007; Lavrov et al., 2017).

In the case of the DDM, instead, the most exploited and effective methods are: Neural Network (NN) (Cheng et al., 2017; Wang et al., 2017), which can be simple shallow networks, sometimes improved with features selection techniques, or Long–Short Term Memory (LSTM) (Deng et al., 2020) network, capable of learning local and big trends in time-series, or Extreme Learning Machine (ELM) (Yu et al., 2014), a shallow network which uses a Least-Square solution instead of back-propagation algorithm for training; Support Vector Machine (SVM) (Kawan et al., 2017; Anguita et al., 2002) with different kernel types, and Minor Component Analysis (MCA) (Zhao et al., 2004).

We decided to select the methods to be presented for each category according to these criteria: recently developed models (from 2010 to 2020) with more citations or models between 2000 and 2010 with at least 15 citations.

For what concerns HMs, this approach has been less investigated in literature and all methods proposed for SM and QP prediction have been reported.

In the following sections, advantages and disadvantages of the PM, DDM, and HM and relevant examples have been analysed in details, as well as the open problems of SM and QP prediction which could lead to future developments. Moreover, for each class of models, tables has been reported summarising the following aspects:

- Input data: the models can process past SMs, propulsion's data, measurements of waves and/or wind data, future waves' predictions, or a combination of all these input data;
- Data origin: synthetic data or real-world data collected during sea-trials by on-board sensors;
- Amount of data: the amount of data exploited to built and validate the models;
- Prediction horizon: the models can produce long-term or short-term predictions;
- Method: the technique used by the models to predict the output;
- Output: whether the models predict SMs or QPs;

- Accuracy: the accuracy obtained by the models;
- Computational requirements: computational time required to make predictions.

Note, finally, that tables cannot be always used as a direct comparison due to the different data and computer configurations used in the different works.

3.1. Physical models

PMs (see Fig. 4(a)) aim at describing SMs and QPs by means of a representation of the physical response of the vessel to exogenous (e.g., propellers and rudders) and endogenous (e.g., wind, wave, and currents) actions (Bergdahl, 2009). Physics-based sea-keeping models are focused on the response of the ship to the wave actions and, specifically, on the prediction of the SMs and the wave loads acting on the ship structures. Though viscous effects certainly play a role in the behaviour of a ship in waves, classical methods used for SM and QP prediction, based on potential flow theory, ignore these effects, and nevertheless provide in general accurate predictions of the SMs, except for the roll motion, for which viscous effects play a dominant role (Connell et al., 2015; Naaijen et al., 2016a).

Comparing PMs with methods based on statistical inference (Deng et al., 2020), PMs are more reliable and generally rather tolerant to extrapolation and, since the relationship between input and output is known a-priory and do not have to be learnt, these models do not require an extensive number of operational measurements. This is an interesting property because a big amount of data is not always available and producing new measurements can be very expensive in some cases (Coraddu et al., 2015); in the case of SM and QP predictions, data have to be collected from on-board sensors during ship's sea trials, which are expensive to organise. However, competence and experience in the field of fluid-dynamics is required to build this kind of models, which is not mandatory in building DDMs, and it is not always easy to get access to this kind of technical details and skills (Coraddu et al., 2017). Moreover, in general, PMs are more computationally expensive than DDMs and sometimes they are not able to reach real-time performances needed for SM and QP predictions, except for LP (Connell et al., 2015) models which are, as we will see, the most exploited ones.

There are several different sea-keeping models and criteria to classify them. The Sea-keeping Committee of the International Towing Tank Conference (ITTC) provides regular reviews of sea-keeping models and has also addressed the issue of classification (Kim et al., 2014, 2017; Crossland et al., 2011). One rather common approach to classification is to consider PL models, PNL models and CFD models. PL models (Connell et al., 2015; Naaijen et al., 2016a; Dannenberg et al., 2009; Feng et al., 2013) are well established and widely used. The main simplification introduced by such models is to assume the hull wet surface to be defined by the ratio between the mean position of the hull and the mean free surface, which allows the linearisation of the boundary conditions of the potential flow problem. A linearity assumption is also made regarding the waves: they are modelled as the superposition of sinusoidal waves of different amplitudes and frequencies. These assumptions allow to solve the sea-keeping problem in the frequency domain and compute the ship response as the superposition of the responses to the sinusoidal components of the wave excitation, thus reducing the complexity of the computations. The attractiveness of PL models, in fact, is that they have relatively low computational requirements and are able to produce near real-time predictions. This is very important, because a full characterisation of the ship behaviour in waves requires considering many different wave's directions and characteristics and thus running many computations. As mentioned above, PL models are widely used. However, there are conditions for which the assumptions of such methods are no longer valid: in high sea states, assuming the hull wet surface to be static is unrealistic and non-linear effects associated to the change in the wet surface over time become important.

PNL methods (Mortola et al., 2011) address the different non-linearities in the ship behaviour that become relevant in high sea states. They are time-domain methods and are all more computationally demanding than PL methods. They are often classified in 'weakly non-linear' and 'fully non-linear methods'. Weakly non-linear methods (Mortola et al., 2011) account for only part of the non-linearities in the ship behaviour (because the radiated and diffracted forces are computed according to the linear model), but they are able to cover very relevant non-linearities and are thus able to provide accurate predictions with a computational time that, though longer than in the linear case, is still lower than the time required by fully non-linear computations.

The most common potential-flow based methods are:

- methods based on the strip theory (ST) (Feng et al., 2013; Mortola et al., 2011): they are 2D methods and can be linear and non linear;
- Boundary Element Methods (BEMs) (Dannenberg et al., 2009): they are 3D methods which require the modelling of the hull and, in some cases, of the free surface, with panels. They can be linear or non-linear. The most used BEM approaches are based on Green functions (Sutulo et al., 2009) or Rankine models (Söding et al., 2012).

In Mortola et al. (2011), for example, the authors propose a non linear time-domain approach based on ST for prediction of SMs and wave loads. The diffraction forces and hydrodynamic coefficients are computed using strip theory for relevant combinations of section immersions and heel angles and the RAOs of heave, pitch, and vertical bending moments (VBM) are then obtained for a container-ship in head waves, in the case of zero speed. However, even if non-linear models are able to cover very relevant non-linearities characterising the ship's response and thus are able to provide accurate predictions, they are computational expensive and often fail to reach on-line performances. For near real time prediction of SMs and QPs, linear models are usually used, as they allow very fast predictions that are not allowed by non-linear models. This is confirmed by an analysis of papers concerning real-time SM and QP predictions for applications on board the ship. Authors of Dannenberg et al. (2009), for example, present a model based on measuring the 3-D wave field one nautical mile from the vessel by means of a X-band radar. These measurements are used as input to a wave propagation model to compute the wave elevations at the location of the vessel up to two minutes ahead. Meanwhile, through a linear 3D model, RAO is computed for heave and pitch motions. After the successful laboratory tests (Naaijen et al., 2009), the system was installed on an 80 m offshore support vessel equipped with a X-band radar and with a bow mounted down-looking radar with an accurate motion sensor unit to provide the true targets (Dannenberg et al., 2009). Despite significant deviations in the actual amplitudes and phasing, the envelope of the motions was predicted correctly till a time window of 120 s.

Authors of Connell et al. (2015), instead, propose a Reduced Order Method (always belonging to PL models category) as predictor of the ship's response using as input the wave predictions obtained by a wave propagation model applied on the resolved wave field provided by the AWSR radar (radar measuring waves up to 5 km of the ship location, allowing wave predictions up to 5 min). Parameters of the model, such as inertia of the body and RAO coefficients, are determined using the ship sea keeping simulation tool AEGIR, which allow several minutes of motion forecast in about 1 s calculation. The system has been tested aboard the R/V Melville vessel: the roll forecasting performance was generally worse than heave and pitch, this because AEGIR is not able to capture viscous effect which much influence roll motion and external models need to be implemented to capture these other important effects, based on empirical formulas.

Authors of Naaijen et al. (2016a) propose a combination of a wave propagation model (based on inverting raw X-band navigation radar data into estimations of the wave elevation) and a linear vessel response

Table 1
Physical models.

Ref.	Method	Input	Data origin	Amount of data	Prediction horizon	Output	Computational requirements	Accuracy
Naaijen et al. (2016a)	PL (BEM)	Predicted wave elevations	X-band radar and motion sensor units	Radar data up to a distance of 1250 m from the radar antenna	80 s	SMs prediction	Not provided	R = 0.67 for roll R = 0.8÷0.9 for the remaining 5DOF
Dannenberg et al. (2009)	PL (BEM)	Predicted wave elevations and measured pitch and heave motions	X-band radar and motion sensor units	Several radar images of 128 × 128 pixels	120 s	QP prediction	13 s on a quad-core PC CPU	Worst trial R > 0.5 Two other trials R > 0.7
Connell et al. (2015)	PL (ROM)	Wave predictions and past SMs data	Advanced Wave Sensing Radar(AWSR) and motion sensors	Series of 20–30 min experiments	30 s	SMs prediction	Few seconds for prediction	$R \simeq 0.7$ for heave $R \simeq 0.67$ for pitch $R \simeq 0.45$ for roll
Feng et al. (2013)	PL (ST)	Regular head waves data	Synthetic data	Not provided	One-step ahead	SMs prediction	Not provided	Maximum error on pitch and heave RAO: 0.2
Sato et al. (2007)	CFD	Incident wave data: wave length, direction, and amplitude	Synthetic data	16 steps	15 steps-ahead	SMs prediction	1.5/3 millions of grid points to process	Maximum error on pitch and heave RAO: 0.15
Lavrov et al. (2017)	CDF	A set of roll oscillations with given amplitude and frequency	Synthetic data	Around 2 min	One-step ahead	SMs prediction	Between 10 and 100 h, depending on the mesh applied	Difference of 10–20% between CFD and BEM (Sutulo et al., 2009) hydrodynamic coefficients
Mortola et al. (2011)	PNL (ST)	Waves (height and amplitude)	Synthetic data	1 h and half	One-step ahead	SMs predictions	Not provided	Maximum discrepancy on pitch and heave RAO: 0.1 (respect to linear frequency methods)

model, to predict SM prediction some tens of seconds up to minutes into the future, depending on radar range and sea state. The method has been validated on data measured by on-board sensors during a field campaign at zero ship's velocity and show accurate results: except for roll, correlations between 0.85÷0.9 were obtained for predicted SMs.

In Feng et al. (2013), an approach based on the Method of Fundamental Solutions (MFS), integrated with frequency domain strip theory, is proposed for predicting ship's response in the frequency domain. Although more sophisticated 3D and time-domain methods are available, MFS is a panel-free and integration-free approach and, as a result, it is mathematically simple, robust and easy for programming and in most cases sufficiently accurate. A comparison with a 3D panel method is performed on experimental data: computed heave RAO agrees well with experimental one, while performances of pitch RAO decrease, increasing the wave length.

In literature, in some works, CFD techniques are sometimes used for sea-keeping computations but they are very computationally expensive with respect to potential flow models, therefore it is seldom used for the computation of SMs in ship design practices. However, they are used for the study of the roll motion (Lavrov et al., 2017) and the derivation of simplified formulations and coefficients to be used in simplified models that can be integrated in potential-flow based models (Wanderley et al., 2007; Uzunoglu and Guedes Soares, 2015; Connell et al., 2015) for the prediction of the sea-keeping performance.

For example, in Lavrov et al. (2017), authors propose the use of CFD computations to identify hydrodynamic coefficients of roll motion and capture their dependence on the ship's topology. In particular, OpenFOAM is used to solve the RANS equations and determine the moment amplitude of forced roll motions of three typical mono-hull 2D sections.

In Sato et al. (2007), a new developed CFD simulation methods (WISDAM-XI programme) is used for the prediction of motion performance of a multi-hull vessel. The ship's motion is given by the solution of the motion equations with the external wave forces and moments from the integration of the pressure and the frictional forces on the hull surface. Only results on experimental data (towing tank tests) are available: heave and pitch motions are predicted with reasonable accuracy, while roll amplitude is under-predicted.

Table 1 summarises the reviewed works on PMs.

Finally, it is worth noting that several factors can influence the prediction horizon of radar remote sensing for ship motion prediction. These factors include the type of radar system, its range, and resolution that can directly impact the prediction horizon (Skolnik, 2008, 1962). For instance, synthetic aperture radar systems generally offer higher resolution and larger coverage areas than traditional radar systems, which may result in longer prediction horizons (Curlander and McDonough, 1991). Moreover, the availability of continuous and up-to-date radar data is crucial for accurate and reliable ship motion predictions. Gaps in data or insufficient coverage can limit the prediction horizon (Headrick et al., 2008). Environmental factors, such as weather conditions, sea state, and other electromagnetic sources, can cause interference and noise in radar signals. High levels of interference and noise can reduce the quality of radar data, which may impact the prediction horizon (Thayaparan and Wernik, 2006). The prediction horizon can also be influenced by the available computational resources and the complexity of data processing techniques. Real-time processing of high-resolution radar data can be computationally intensive, and limited computational resources may constrain the prediction horizon (Long et al., 2019; Moreira, 1992). The integration of radar remote sensing data with other data sources, such as meteorological data, oceanographic data, or data from other remote sensing technologies, can improve the overall accuracy and extend the prediction horizon. However, the quality and timeliness of these additional data sources can also impact the prediction horizon (Huang et al., 2017; Klemas, 2012).

Various wave prediction methods (Massel, 1996; Wijaya et al., 2015), such as buoys, coherent radar, and non-coherent radar, offer distinct advantages and limitations in their ability to accurately predict and monitor ocean wave dynamics. In the following we provide a brief overview and comparison of these three methods, focusing on their respective strengths and weaknesses.

Buoys (Steele et al., 1992; O'Reilly et al., 1996) provide direct and accurate measurements of wave height, period, and direction, making them a reliable source of wave data and can transmit wave data in real-time, enabling quick updates and timely predictions. Moreover, they can be deployed for extended periods, facilitating long-term monitoring of wave conditions in a specific location (Richardson et al., 1963). Buoys are effective wave measurement devices, however, they do not fully answer the purpose of measuring waves for motion prediction on a vessel in operations. Vessels in operations may pass close to wave buoys but most of the time travel outside the areas covered by fixed buoy installations. Additionally, buoys are characterised by limited spatial coverage, providing localised measurements, which may not capture the broader spatial variability of wave conditions. They require regular maintenance and can be subject to damage or loss due to harsh weather or vandalism, resulting in additional costs. Finally, they are susceptible to biofouling, potentially affecting their performance and data accuracy (Krogstad et al., 1999).

Wave information for motion/QP prediction needs to be collected using technologies that can be installed on board ships, so that information is always available, wherever the ship happens to be, within, of course, the limits of the chosen technology. The radar-based technologies are those that currently best answer the need to have an almost constant availability of wave data on board an operating ship. They feature limitations in reach (how far the waves can be detected) and accuracy, which might be hopefully overcome through improvements/developments in radar signal processing. Coherent radar systems (Hasselmann et al., 2012; Quach et al., 2020), such as synthetic aperture radar, can provide high-resolution data on ocean surface features, enabling more accurate wave predictions. They can operate effectively in various weather conditions, including rain, fog, and darkness, ensuring continuous and reliable data acquisition, and can be used for a wide range of applications, including wave prediction, ship motion prediction, oil spill detection, and oceanographic studies. Coherent radar can be more expensive to deploy and maintain than other wave prediction methods, particularly for large-scale operations and often requires sophisticated processing and analysis techniques, which can be computationally intensive and require specialised expertise (Singh et al., 2021).

Non-coherent radar (Rosenberg and Bocquet, 2017; Vicen-Bueno et al., 2012) can monitor larger areas than buoys, providing a broader understanding of wave conditions. They are generally less expensive than coherent radar systems, making them more accessible for wave prediction applications. Unfortunately, non-coherent radar systems typically have lower resolution and accuracy than coherent radar systems, which can impact the quality of wave predictions. Finally, non-coherent radar systems primarily measure surface features, making it difficult to obtain information about subsurface wave dynamics (Cornejo-Bueno et al., 2016; Naaijen et al., 2016b).

3.2. Data-driven models

DDMs, differently from PMs, use the historical collection of inputs and outputs (data) of the ship system to make SM and QP predictions. In fact, these methods do not require any a-priory knowledge of the underlying physical phenomenon, but they use data to learn the relationship between input and output and induce the model, then employ the learnt model to make predictions on new measured input data (Hastie et al., 2009) (see Fig. 4(b)). This approach have several advantages but also some disadvantages.

The first advantage is that DDMs, learning from data, can capture important relationships for the calculation of the prediction that PMs ignore or are not able to model, or can discover that expected significant variables result not to be relevant for the performance of the prediction. For example, author of Coraddu et al. (2017) found that, for the prediction of the ship's fuel consumption, wind speed and direction, expected to contribute significantly to the overall performance of the model, are not among the most relevant features which influence the output. This could suggest that wind speed and direction are not appropriate predictors for modelling this type of effects, contrarily to what often assumed in relevant literature. Another advantage of learning from data is that DDMs, thanks to the continual acquisition of real-world data, are able to change and correct their structure dynamically in order to optimise the model's prediction by exploiting the new acquired data (on-line optimisation) (Yu et al., 2014). PM, instead, have a fixed structure defined a-priory on the base of the physical knowledge of the ship system and cannot take into account varying real-world operating conditions.

Let us now discuss also the disadvantages. Since the models are not supported by any physical interpretation, a significant amount of data are required to build a reliable model and a lot of measurements of the real phenomenon are not always available or expensive to obtain. For example, authors of Kawan et al. (2017) exploited 3 years of row data coming from on-board sensors to build a reliable model. Moreover, as already stated, being built only on historical observations, the DDM is less reliable respect to PMs, in fact it works well on average, but it could produce not physically plausible predictions in some cases (Alber et al., 2019). From a computational point of view, these models have an expensive training phase(i.e, the phase of the construction of the model), but this phase is performed only one time and once the model is trained, the prediction is produced in few seconds (Liu et al., 2017). From a cognitive point of view, instead, DDMs are, in general, less interpretable than PMs and HMs. In fact, NNs (Deng et al., 2020) and SVMs (Anguita et al., 2002), which are the most exploited ML techniques for SM and QP prediction, are both black-box approaches (i.e., it is not possible to understand how the inputs affect the output and why the model produced that particular result).

As previously stated, currently, in the field of SM and QP prediction, the most exploited and effective methods proposed in the literature are NNs and SVMs. From 1980 to 2000, models using Kalman filtering techniques (Triantafyllou et al., 1983), and Auto-Regressive (AR) models (Yumori, 1981), which forecast the variable of interest using a linear combination of past values of the output, have been the methods mostly exploited to describe SMs. However, Kalman filtering works only for Gaussian noise processes and AR models, being based on a linear combination of past values of SMs, allowing to reach short prediction horizons (at maximum 10 s) and are not suitable for high dimensional non-linear phenomena. Therefore, NNs (Peña et al., 2011; Yu et al., 2014) and SVMs (Liu et al., 2019) has gained attention in the field of SM and QP prediction. These methods, in fact, are able to learn complex nonlinear relationships between input and output parameters, such as the one which characterises endogenous and exogenous stresses and ship's response. Moreover, with a sufficient amount of data, they both have good generalisation capability and produce very accurate predictions, and they could reach relatively long prediction horizon (De Masi et al., 2011). SVM, in particular, is a good candidate for hardware realisation (Anguita et al., 2000) and embedded systems reaching real-time performances even during the learning phase. Building a NN, instead, is computationally expensive and the cost grows increasing the number of hidden neurons and the dimensionality of the input data (i.e., features). Therefore, models which combine NNs with techniques of features' selection (Cheng et al., 2017) and ELM network (Yu et al., 2014), which avoid the expensive gradient-descent based learning phase of NN (input weights are randomly selected and output weights are analytically calculated), have been proposed in the literature in order to reduce the computational effort of the NN learning phase. Moreover, since the problem of SM and QP prediction deals with time-series data, also Recurrent NN have been proposed in the literature to approach the problem, which learn data long-term dependencies by remembering past information while training; in particular LSTM (Deng et al., 2020) and IDNN (Wang et al., 2017).

Several examples of DDMs, based on the above mentioned approaches, have been analysed.

For example, authors of De Masi et al. (2011) propose a NN with a Gaussian function as activation function of the hidden layer. No wave information is used in the present work, but the Hilbert transform has been applied to heave motions to identify the envelope (low frequency components) of these vessel motions, which, being strictly related to wave envelope, may be considered an indication of wave groups. The algorithm has been tested on data collected during several sea trails and, over a prediction time window of 122 s, accurate predictions (RMSE below 0.6) have been obtained till 40 s, in particular RMSE below 0.2 within the first 20 s.

Also authors of Peña et al. (2011) propose an ANN, but with two hidden layers and sigmoid functions as activation functions. They obtain an RMSE of 0.2 at 40 s on regular waves conditions. However, ANN requires a time-consuming training to obtain an accurate prediction and computational effort increase with the increasing of the network's dimensions.

Therefore, authors of Cheng et al. (2017) propose a NN, with 16 hidden nodes and hyperbolic tangent as activation function, combined with sensitivity analysis (SA) techniques in order to reduce the features to be processed by the network. The authors compare the solution with a full NN: prediction error reduces of 95% and the computation time of 98% respect to full NN. The authors, in particular, compare two SA algorithms, Garson and EFAST; the first explores the response of the model's output to a small change of one parameter from its nominal value, while the other features remain constant; the second estimates the effect of input parameters across the whole input parameter space. Authors found that EFAST method gives better results respect to Garson in predictions of both linear and non-linear system. Therefore, EFAST has been chosen for heading prediction: surge velocity and ship's position are found as the features that much influence the heading.

Authors of Deng et al. (2020), instead, propose a network composed by one LSTM layer (128 hidden nodes) and two layers of dense NN(128-1) applied on the output of the recurrent network. Mean Squared Error (MSE) is selected as the loss function for model selection (optimisation of hyper-parameters). The model has been tested against numerical and experimental RAO-based methods on synthetic data and it outperforms both.

In Anguita et al. (2002), instead, the SVM algorithm is used as time series predictor. The purpose of the SVM is to learn the signal dynamic by observing historical examples and then generate a prediction of the near-future dynamics. The critical element which much affects the accuracy of the prediction is the model selection phase: the error function used in this work for the model selection resembles the e-insensitive loss function of the SVM, a tube inside which the prediction is considered correct and outside the error is accounted according to the error committed on the phases of the first two harmonics of the signals. This because, in the considered application of landing period designator systems, the shape of the prediction is more interesting than the actual value and a simple MSE criterion do not take into account the difference in shape between the true and predicted signals.

Motivated by nonlinear learning ability of Support Vector Regression (SVR) model and the ability of processing non-stationary data of empirical mode decomposition (EMD), authors of Nie et al. (2020) propose a model based on the integration of these techniques for short-term prediction of SMs. In particular, the model uses mirror symmetry and SVR algorithm to eliminate EMD boundary effect which usually decreases the prediction accuracy.

In Kawan et al. (2017), the measured row data of motions are cleaned using noise reduction, re-sampling and data continuity techniques, then the important features are selected and give as inputs to a SVM, which has to learn the relationship between pitch and the other SMs. The important features are chosen according to the correlation values between the feature and the output. For the considered case study, they found that surge, sway, yaw, and roll velocity, x and y position, heading, and roll angle have a significant relation for the prediction of the pitch.

In Yu et al. (2014), an improved online sequential extreme learning machine (OS-ELM) is applied on roll motions prediction. Instead of the time-consuming iterative learning process typical of NN, ELM uses least squares method to acquire network weights in only one step and without iterative turning, which make it much faster than traditional back-propagation (BP) NNs. Moreover, in this work, the OS-ELM is improved by temporal difference (TD) reinforcement learning method: when the new observation is available on the sequence, the prediction is adjusted to a more accurate answer based on past errors which are considered as rewards for the algorithm. Under this mechanism, the system has a capacity for self-driven learning. This increased the accuracy of the prediction: the authors found that, on data collected during sea trails, respect to classical OS-ELM, the RMSE reduces of 4%, at the cost of an increase of 65% of the computational time, but time computing is still very low (0.00129 s).

Authors of Zhao et al. (2004), instead, propose a high-performance SMs prediction model using Minor Component Analysis (MCA) algorithm. MCA is, besides a prediction model, a feature selection technique: the minor components, i.e., the directions of very small variation (smallest variance) and so less sensible to noise, are selected. The authors compare the model with auto-regressive (AR) model, NN and Wiener filter and the model outperforms all of them: the RMSE at 20 s-ahead prediction decreases of 72% respect to the best one among the three. As an additional advantage, training and prediction time of MCA are short(0.09 s for prediction and 40 s for training) and constant respect to the prediction window's length.

Authors of Wang et al. (2017) propose an input-delay neural network (IDNN) using as input past motions data and gyroscopes measurements which, they found, can significantly decrease the prediction error (RMSE of roll of 0.51 deg without gyroscopes data, 0.28 deg with these measurements). However, the prediction horizon is small, but it is possible to increase it increasing the number of hidden layer and the past values considered, obviously at the cost of increasing the computational time.

Aiming to lengthen prediction time and improve prediction accuracy of classical approach, such as ARMA and radial basis functions (RBF) NN, authors of Liu et al. (2019) propose an online prediction method based on Least Square Support Vector Machine (LSSVM). In LSSVM, the ϵ-insensitive loss function does not grow linearly, but quadratically outside the ϵ-tube, so the topic to solve a quadratic programming problem is changed into solving a set of linear equations and the learning difficulty in SVM is reduced. In order to acquire optimal parameters for LSSVM the genetic algorithm (GA) is adopted. The model has been tested on real data collected during a sea trial, but using the parameters optimised by the GA algorithm on simulated data: it provides a percentage error of 23% in good sea conditions and 25% in adverse ones.

Table 2 summarises the reviewed works on DDMs.

Table 2
Data-driven models.

Ref.	Method	Input	Data origin	Amount of data	Prediction horizon	Output	Computa-tional requirements	Accuracy
De Masi et al. (2011)	NN	Time series (122 s) of heave motions	On-board sensors	1 day	40 s	SMs prediction	Immediate	RMSE: 0.6 m at 40 s 0.1 m at 20 s
Deng et al. (2020)	NN	Time series (80 s) of 135° incident waves	Synthetic data	3-h	One-step ahead (1 s)	SMs prediction	Immediate	MSE: 0.47 for heave 0.85 for roll 0.77 for pitch (losses are non-dimensional as the dataset has been scaled prior to the training process)
Anguita et al. (2002)	SVM	SMs past values	On-board sensors	1-h	Roll: 10 s Pitch: 4-5 s	SMs prediction	Immediate	Maximum error below 0.1° till 10 s for pitch and 5 s for roll
Kawan et al. (2017)	SVM	Current values of SMs and relevant velocities	On-board sensors	Three years	One-step ahead	SMs prediction	Immediate	RMSE: around 0.1°
Yu et al. (2014)	NN	Past (7 s) roll motions	On-board sensors	17 min	One-step ahead (1 s)	SMs prediction	Immediate	RMSE: 0.3621°
Zhao et al. (2004)	MCA	Past (400 s) heave motions	Synthetic data	50 min	20 s	SMs prediction	Immediate	RMSE at 5 s: 0.0538 m RMSE at 20 s: 0.0540 m
Peña et al. (2011)	NN	Wave amplitude data and relevant roll motions	Synthetic data	1 h and 45 min (for tank test)	10 s	SMs prediction	Immediate	MSE at 10 s: $12.04 \cdot 10^{-4}$ rad^2 (with roll resonance) $3.76 \cdot 10^{-4}$ rad^2 (no roll resonance)
Cheng et al. (2017)	NN	Current values of SMs, ship's position, and thruster status	On-board sensors	Not provided	One-step ahead	SMs prediction	Immediate	RMSE: 1.71°
Wang et al. (2017)	NN	Past SMs (roll, pitch, and yaw) and relevant velocities	Synthetic data	23 min	4 s	SMs prediction	Immediate	RMSE at 4 s (10 hidden neurons and 10 steps-back input data): roll: 1.170° pitch: 0.390° yaw: 0.750°
Liu et al. (2019)	SVM	Pitch and heave past motions values (21 steps back)	Synthetic data	10 min	12 s	SMs prediction	Immediate	Percentage error at 12 s for model 3 (with random noise in the input): pitch 83.64% heave 83.92%
Nie et al. (2020)	SVM	Past SMs (250 s)	On-board sensors	17 min	50 s	SMs prediction	Immediate	RMSE pitch: 0.28° RMSE roll: 0.07°

3.3. Hybrid models

HMs are a combination of PMs and DDMs (see Fig. 4(c)). This implies modifying a DDM in a way to include the mechanistic knowledge of the system.

There are three main ways to do that:

- The DDM is used to estimate the parameters of the physical model which is then used for prediction or, in alternative, to produce prediction after having training the model on expensive CFD simulations, in order to learn physical effects which the PM is not able to model because it would result in too complex models with consequent computational and numerical issues (Del Águila Ferrandis et al., 2021; Ra and Whang, 2006);
- The mechanistic knowledge of the real system can be encapsulated in the input variables of DDM (adding, as input feature, the output of the PM) in order to correct predictions made by the deterministic model (Skulstad et al., 2021; Leifsson et al., 2008; Nie et al., 2020);
- Apply the physical knowledge of the relationships between input and output as constraint for the DDM, in order to produce a DDM more similar to the true system (Coraddu et al., 2017).

Since HMs are, by construction, a combination of PMs and DDMs, they allow exploiting both the mechanistic knowledge and the available measurements of the underlying physical phenomenon; therefore, they are able to take the best from both the worlds. In fact, on the one hand, they require a smaller amount of historical data to obtain a model as accurate as pure DDMs, since the hint on the underlying physical system reduce the number of samples needed for training (Del Águila Ferrandis et al., 2021). Moreover, HMs, starting from an already good approximation of the phenomenon provided by the PM, are much less prone to produce not physically plausible predictions respect to DDMs (Skulstad et al., 2021). On the other hand, HMs are more accurate than PMs with similar computational time and power requirements since they are able to learn from historical observations of the real system improving the model's accuracy without increasing the complexity of the physical model. In particular, according to how the HM is constructed, the phase of making predictions could be immediate, as per DDMs (Del Águila Ferrandis et al., 2021; Nie et al., 2020).

Nevertheless, note that the use of HMs poses some challenges. The first one is that the PMs, leveraged by the DDMs in the HMs, need to meet two contradicting goals: on the one hand, it should be computationally efficient enough not to make the final HMs too expensive, and on the other, it should be accurate enough to provide valuable insights into the HMs. In fact, fast PMs are usually not accurate and accurate PMs are usually computationally demanding, preventing real-time predictions. The second challenge is that the DDMs, leveraged in the HMs, must be able to simultaneously fully exploit the information in the data and the PMs over-performing them. The third one is more fundamental: sometimes DDMs and PMs are not ready to be joined in HMs, resulting in a need for deep knowledge of both approaches requiring a multidisciplinary approach which is often hard to find.

For these reasons, the modelling approach of HM has been less investigated in the literature, and only recently it gained attention for the good properties discussed above (Del Águila Ferrandis et al., 2021; Skulstad et al., 2021; Nie et al., 2020). The most exploited ML algorithm used to produce the HM is the LSTM network. For example, authors of Del Águila Ferrandis et al. (2021) propose an hybrid method based on a viscous model (Unsteady Reynolds Averaged Navier–Stokes (URANS) solver) and a LSTM network in order to learn nonlinear viscous damping effects which mostly affect roll motions. In fact, commonly used PMs based on potential flow theory do not take into account these effects and this reduces the accuracy on the prediction, especially for roll motions. In this work, the NN is trained offline with expensive CFD simulations produced by the URANS solver so that the network can learn also viscous and non-linear effects. Training is of course time consuming, but online predictions can be obtained at a fraction of seconds and yields truly real-time accurate predictions.

LSTM algorithm has been exploited also by authors of Skulstad et al. (2021). The authors propose a tool for on-board support that produces position predictions based on the integration of a supervised ML model (LSTM) into the ship dynamic model (manoeuvring model of Fossen, 2011). The final prediction of the HM is the sum of the position prediction made by the PM and the error compensation for the unmodelled effects of the PM made by the ML model, for example shallow water effects, wave and sea currents contributions which the constructed PM ignore. Although the black-box nature of the LSTM does not allow for direct insight into what causes the vessel model predictions to deviate, it compensates for the PM deviations, producing more accurate predictions: on data collected during a sea-trial, the MAE in the position's predictions was reduced by about 4 m respect to the result produced by the PM alone.

Authors of Al-Ani et al. (2019), Al-Ani and Belmont (2021), instead, present a probabilistic model that describes the probability distribution of the QP for a selected wave height, based on the sea power spectral density and a-priory defined probability density functions (PDFs) known in literature (physical knowledge hint to the model): Naess (1985), Rice (1940) and Cavanie et al. (1976). The quantities predicted are the QP of the waves' motions, not of the SMs which are slightly different because the ship's response is influenced also by other factors, but in some cases is a good approximation and the authors find a good results on real-world data. Both the articles are based on the Kimura's approach: the probability P of having r successive waves of height < h (definition of QP) is defined as $p_{L(h)}p^{r-1}_{LL(h)}$, where $p_{L(h)}$ is the probability of a wave being below the threshold h and $p_{LL(h)}$ is the conditional probability of successive low waves. But (Al-Ani and Belmont, 2021) extends and completes the work presented in Al-Ani et al. (2019), providing the probability of QP of a specified time duration instead to merely the number of successive quiescent waves, as in Al-Ani et al. (2019). Moreover, the results presented in Al-Ani et al. (2019) are limited to a very small class of oceanographic spectral forms, while Al-Ani and Belmont (2021) employs numerical techniques to obtain results for any arbitrary spectra, including measured data from sea-trials.

Table 3 summarises the reviewed works on HMs.

4. Open problems and future perspectives

This section summarises the open problems and future perspectives in the context of SM and QP prediction.

The main open problem raised in most of the referenced works is how to increase the prediction horizon. In fact, most of the current works, especially among the DDMs (Peña et al., 2011), are able to achieve a satisfying accuracy one for limited horizons (in general below 10 s). As discussed in Section 2, the capability to provide accurate and reliable predictions for a sufficiently large time horizon (e.g., 30 s for helicopter landing) is one of the more important desiderata in SM and QP prediction, since it would allow to effectively plan the marine operations. Most of the current models with short prediction horizon used just past motions data as inputs, without information on waves motion (past values and forecasts) (Wang et al., 2017). Therefore, using also this information would possibility increase the accuracy in larger prediction horizon. Moreover, many of the developed models have been designed to forecast one step (1 s) ahead (Kawan et al., 2017; Yu et al., 2014) and then improperly applied inductively on the predictions to make longer forecasts. Designing native multi-step models would increase the accuracy for larger prediction horizons. However, the best results in terms of the length of the prediction horizon have been obtained by exploiting HMs (Del Águila Ferrandis et al., 2021). Therefore, future research should be performed on this kind of models since, until now, they have been less investigated and applied. It is worth noting that, for HMs, not all PMs can be exploited. The ones exhibiting state-of-the-art accuracy are too computationally expensive, nonetheless, less accurate and complex PMs can be quite computationally aware, being ideal candidates for the HMs.

For what concerns the future perspectives of AI (Nilsson, 2014; Haslum et al., 2019; Barr and Feigenbaum, 2014) for SM and QP prediction, we think that there is still a large space for improvements. The schema of Fig. 5 represents how AI can support the decision and not simply estimate future events. In fact the final goal of AI is to partially or even fully automatise the decision processes. In our case then, we would like to automatically plan the marine operation based on the SM/QP predictions. For this purpose different steps needs to be automatised. The first step is the development of SM/QP predictive models as described in this review. However, these models are not able to fully describe the constraint and the preferences of the maritime operations but they are just able to make prediction on narrow phenomena for a limited time horizon. To model the maritime operation and to optimise the decision processes we need to rely on Model Based Reasoning (e.g., Planning Domain Definition Language Haslum et al., 2019 or Answer Set Programming Brewka et al., 2011), in order to combine the predictions with the domain knowledge of the maritime procedures. Thanks to the combination of Model Based Reasoning and Predictive Models we can generate Casual Models that can be used to generate scenarios and select the plans which deliver best performance for the decision makers to take actions. In fact, different valid operation strategies exist to obtain the desired outcome, but, depending on

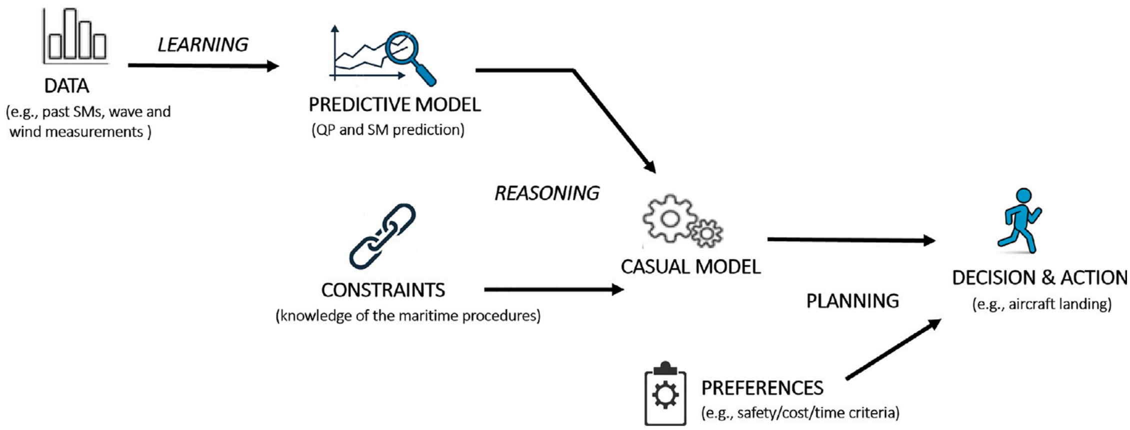


Fig. 5. AI for supporting and/or fully automating the decision processes.

Table 3
Hybrid models.

Ref.	Method	Input	Data origin	Amount of data	Prediction horizon	Output	Computa-tional requirements	Accuracy
Al-Ani et al. (2019)	Probabilis-tic model	Time series of sea wave elevation (Sea State 1÷2)	Synthetic data	4 days for each sea condition	Depends on the prediction horizon of wave spectrum data	QP identification	Only the computation cost for wave prediction	Match between the collected statistics and the probability model decreases increasing the target QP duration
Al-Ani and Belmont (2021)	Probabilis-tic model	Time series of sea wave elevation with different sea states	Measured wave data from two buoys	4 days for each sea condition	Depends on the prediction horizon of wave spectrum data	QP identification	Only the computation cost for wave prediction	Match between the collected statistics and the probability model decreases increasing the target QP duration
Del Águila Ferrandis et al. (2021)	PM + LSTM	Time series of wave elevations and corre-sponding motion data	CFD simulations	120 h of simulations	About 80 s	SMs prediction	Immediate	Overall RSE: 0.165 (for 4 layers and 90 hidden neurons)
Skulstad et al. (2021)	PM + LSTM	Relative wind direction and speed, SMs and thruster status(1000 s)	On-board sensors	1 year	30 s	SMs prediction	Immediate	MAE at 30 s: 8.85 m

operators preferences and safety/cost/time criteria some strategies can be preferable.

For example, deciding when to plan an aircraft, requires first to forecast a WP of at least 30 s (Riola et al., 2011). Then, different landing strategies can be actuated base on the criteria to optimise. Supporting the operator, who is in charge to take the final decision, with different optimal scenarios equipped with reliable quantitative estimations of time/risk whorl both facilitate his work and reduce, on average, mistakes. Therefore, even not fully automating the processes (like in this example) but simply supporting the operators with different optimal strategies computed by a machine can be of great help.

5. Conclusions

The scope of this work was to review the methods proposed in literature for SM and QP prediction. For this reason we first grouped the approaches in three families: PMs, DDMs, and HMs. PMs are based fully on the physical knowledge of the phenomena, DDMs fully rely on historical data to learn the desired predictor, while HMs are able to exploit both information. Then, for each family, we listed the pros and cons and we review the models developed in the last 10 years with more citations and models between 2000 and 2010 with at least 15 citations.

As take-home message it is possible to state that DDMs have the advantage to provide near real-time prediction but, in general, for limited prediction horizon (Anguita et al., 2002); this is mainly due to the fact that the DDMs proposed in literature are usually fed with past SMs data with no information on past or future waves' data, which could increase the prediction horizon. PMs, instead, reached interesting results in terms of prediction horizon (120 s in Dannenberg et al. (2009)) since they exploit waves' motion data and waves' prediction, but they are, in general, computationally expensive and less accurate, especially on roll motions prediction, than DDMs. HMs offer a compromise between these two approaches obtaining good results in terms of accuracy, prediction horizon, and computational requirements (Del Águila Ferrandis et al., 2021), even if they are far less studied.

This variety of applications and works developed for SM and QP prediction clearly shows the relevance of the topic in maritime operations. In fact, being able to predict sufficiently in advance SMs and QPs is of paramount importance, since it would allow to improve safety and efficiency of, e.g., landing and take-off on aircraft carriers, transfer of cargo, and mating operations between ships. Accurate and reliable SMs and QPs prediction would allow to increase operability allowing to perform these sea-sensitive operations also in adverse weather conditions reducing the need for postponing or cancelling. Therefore we can say that this topic is crucial both for research and industry.

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.

Data availability

No data was used for the research described in the article.

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