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Incorporating Approximate Dynamics Into Data-Driven Calibrator: A Representative Model for Ship Maneuvering Prediction

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***Abstract*—High-fidelity models capable of accurately predicting ship motion are critical for promoting innovation and efficiency in the maritime industry. However, creating an advanced model that comprehensively represents the system and its interaction with dynamic environments has always been challenging. Many models provide partial knowledge about a system. To handle the deficiency and improve model fidelity, we propose a hybrid modeling methodology, in which prior knowledge describing the ship dynamic effects is incorporated into a data-driven calibrator, yielding a representative model with high predictive capability. Enabled by the integration of model estimated ship states into the calibrator, the informative information could be interpreted and carried forward. Simulation and full-scale experiments are conducted on the research vessel Gunnerus to exemplify the concept. A best available numerical model and a neural network are prepared to be the foundation and calibrator, respectively. Experiment results show that the cooperative model greatly improves the predictive capability of the research vessel. From the ship modeling perspective, this study provides new insights by bridging the gap between two separate domains: model-based and data-driven.**

***Index Terms*—Ship motion prediction, hybrid, representative model, preliminary knowledge, machine learning.**

I. Introduction

THE maritime industry is entering an era of digitization [1]. Ship autonomy and ship intelligence are hot topics for both industry and academics. In fact, ship intelligence has been listed as an essential area of the digital agenda, one of the European growth strategy pillars. Digital twins are a major part of this agenda as they are among the most promising enabling technologies for realizing high-level automation in ship design and operation. Thus innovation and efficiency within interacting subsystems as well as within the interaction between physical and virtual spaces is needed [2]. Today's maritime engineering systems are operating in highly dynamic environments. Twin ship models are supposed to best describe the time-varying status of vessels and accurately predict future behaviors. Developing such models appears significant for ship maintenance operations, as well as motion planning in multi-ship systems [3].

The first attempts to create predictive ship models relied on ship dynamic principles. Simulation models are derived to capture as much dynamics and describe the process interacting with subsystems or stochastic environments. Such methods can be powerful due to the dependence on the deep understanding of the ship system. However, the implementation of dynamic models in ship maneuvers can be complex due to the associated nonlinear hydrodynamic forces and moments. Often, the respective vessel parameters cannot be measured or identified. Sutulo et al. [4] discussed several existing popular empiric methods for predicting maneuvering properties of a benchmark ship and found that, in general applications, universal empiric methods could result in unacceptable prediction uncertainties. They suggested using these methods with great care and preferably tuning them on prototype ships prior to applying them. From the practical view, models can also be effort-consuming to develop since tuning a ship hydrodynamic model requires a good deal of time, laborious experiments, and extensive research by experts. Also, the effect of unknown perturbations from uncertain ocean environments on the model fidelity is always irritating but cannot be ignored. On this point, one another challenge that is handling such dynamic uncertainties in developing reliable models arise. As a consequence of these concerns and the desire to create high-fidelity models, data-driven modeling has been established.

Data-driven modeling methods outperform alternatives in estimating nonlinear systems and do not necessarily face the difficulties that affect model-based approaches. They rely solely on a substantial amount of observation data to train the black-box model, and thus little priori knowledge of the modeled system is required. As an end-to-end technique, these methods implicitly model the dependencies of input and output variables. Given the technological advances in data acquisition, data-driven techniques are increasingly applied to construct predictive models and forecast short or long term future ship states. For example, Li et al. [5] constructed an NN model through sensitivity analysis to produce time series prediction of ship motion and analyzed the impact of different learning strategies on prediction performance. This method works well from the forecasting accuracy perspective, but it makes it difficult to inspect the modeled system. The consequent implicit

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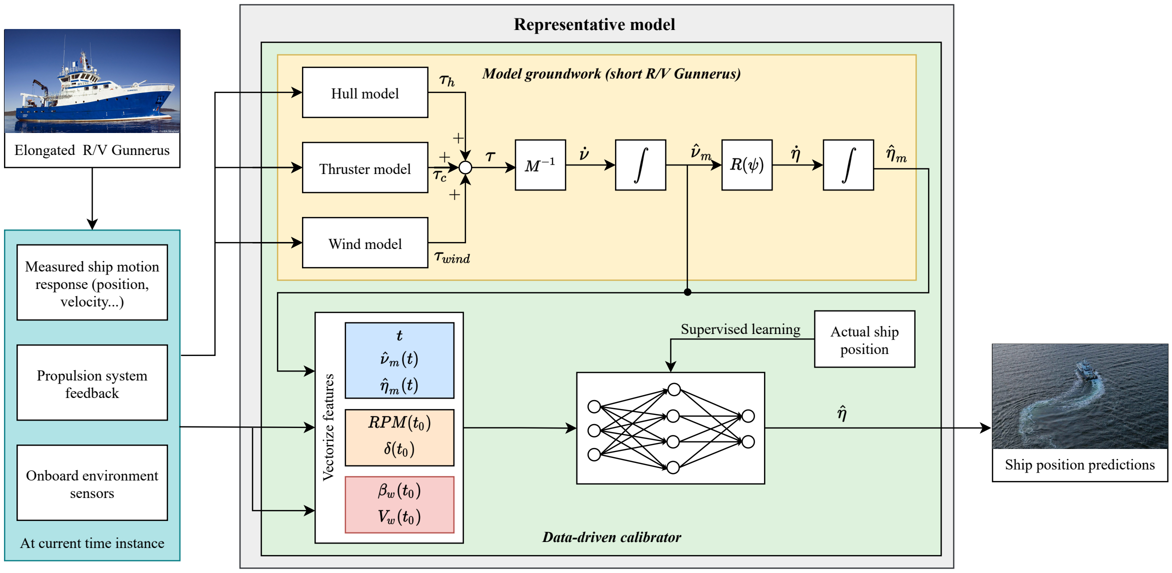

Fig. 1: A complete flowchart showing the incorporating of approximate dynamics into the data-driven calibrator.

situation seems not to be readily interpretive. Moreover, classic data-driven predictive models purely depend on the sample data, which implies that the quality of training data largely determines the accuracy and performance of the obtained model. The performance can quickly deteriorate when the data sets are less balanced or unusual situations not within the training data regime arise.

In order to address the structure of prior knowledge and flexibility of data-driven approaches, this paper presents a hybrid method to reinforce a partially accessible model. It is expected that incorporating approximate dynamics into the data-driven calibrator will yield a representative model that has higher fidelity, better interpretability, and less dependency on data quality. This will be achieved by assuming a cognitive model of the ship available so that information about ship states can be incorporated into the training phase of the calibrator as an auxiliary input. The preliminary ship dynamics is provided by a best available simulation model of the research vessel (R/V) Gunnerus, which went through an elongation in 2019. Before the elongation, the vessel was well modeled and verified through sea trials [6], thus making it the best-available candidate model for the ship after elongation, which was as yet unmodeled. The recorded data embracing the reference model is applied to learn how the reference model can be transferred into a representative model of the elongated ship. The proposed hybrid methodology will be verified in both simulator and full-scale trials. The major contributions of this work are summarized as follows:

- Proposing a novel model-data-hybrid structure wrapping data around an approximate knowledge model to implement a representative model for ship maneuvering prediction.
- A best available simulation model is adopted to prioritize and forward preliminary ship knowledge.
- Verifying the proposed approach in full-scale ship maneuver experiments.

The remainder of the paper is structured as follows. Recent and related work of ship motion prediction is introduced in Section II. Section III is dedicated to present the proposed hybrid prediction methodology. In Section IV, to demonstrate the principles and effectiveness of method, experiments are conducted in both simulator and sea trial, and experimental results are presented and discussed. Finally, in Section V, concluding remarks and possible extensions of the work are discussed.

II. Related Work

A. Model based prediction

The predictive models can be formulated based on either a kinematic/dynamic model or a statistical model. The vessel dynamics have always been strongly associated with navigational status and environmental conditions. Thus the deterministic models could only be reliable subject to specific scenarios and environment configurations. For example, Zhang et al. [7] developed a numerical simulation model for a ship maneuvering in regular waves that introduced a decomposition method to deal with the second-order wave loads. In [8], the author proposed an extended state observer to estimate the unknown relative velocities with respect to the ocean currents in real life. Triantafyllou et al. [9] applied Kalman Filter techniques to predict the vessel motions and they found that the performance of the resulting estimator primarily depended on an accurate sea spectrum model, which required computational efforts in that the transfer function between ship dynamics and sea elevation are complex.

The auto-regressive (AR) model is a type of time-series analysis that is widely applied to various areas of forecasting. It is developed on the past states of the variables and is of good prediction performance, especially for stationary processes. For instance, Yang [10] applied the AR model to predict the vertical displacement of an unmanned aerial vehicle landing deck in the presence of the stochastic sea state. Such statistic models spare the input environment information but have a stringent requirement on the predefined model, which implies that the models are hard to fit changing operational scenarios as well as high sea conditions [11].

B. Data-driven prediction

It is noted that not all data-involved methods are data-driven, but we prefer data-driven methods that employ techniques such as big data, machine learning, and deep learning. Examples are categorized into two branches according to their modeling process.

1) Supervised learning: where a labeled data set is provided to train and evaluate a model. The most applied models are neural networks, and examples of predicting ship responses are reported in [12], [13]. Besides, the long short-term memory deep neural network is also popular when dealing with time series predictions either as an end-to-end model [14] or a compensative model [15]. An example of utilizing clustering techniques is presented in [16]. The authors implemented a k-nearest neighbor classifier to predict ships' routes and tested it on automatic identification system data. The support vector machine is another popular kernel-based approach that is widely used for constructing predictive models [17] and estimating ship states [18].

2) Unsupervised learning: where no labeled data is provided such that the algorithm tries to extract features and patterns on its own. In [19], the authors built an unsupervised ship trajectory model based on existing compression and clustering techniques. The model they trained was fit for a particular scenario and outperformed baseline predictors. Chen et al. [20] presented an unsupervised approach of ship movement trajectory prediction. In their algorithm, a training model is not necessary. Therefore it could provide a fast, reliable, and accurate trajectory predictions.

The principal advantage of the methods mentioned above is the ability of modeling nonlinearities and uncertainties, but they have drawbacks of correlating the physical properties, which would not be readily interpretive.

III. METHODOLOGY

This section will introduce the proposed model-data-hybrid cooperative modeling framework in detail and explain how they are constructed to predict the future ship motion.

A. Hybrid predictive model

As the name suggests, the hybrid cooperative model contains two complementary parts originating from two separate domains: model-based and data-driven. The way they collaborate can be expressed as:

$$\begin{aligned} \dot{X} &= g(X,u) \\ y &= f(X,u,g(X,u)) \end{aligned} \tag{1}$$

where X is the state of the rough system. u and y are registered as representative system control and output, respectively. $g(\cdot)$ represents the preliminary model based on physical disciplines, and the output of the reference model is integrated as an additional input to the neural network model. $f(\cdot)$ is the data-driven model that describes the transferring relationship from the priori model to the representative model of the new system.

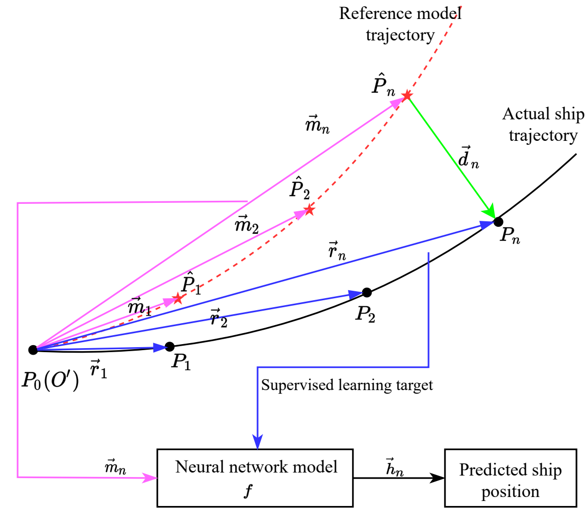

Fig. 2: Illustration of the data-driven calibration concept.

The complete flowchart of the proposed cooperative model in this context is shown in Fig. 1. The model groundwork (top yellow box) is built on a hydrodynamic model of a similar vessel concerning the target ship. It serves to provide approximate ship states $\hat{X} = [\hat{\eta}_m, \hat{\nu}_m]^T$ reacting to the control command and environment configuration. $[RPM(t_0), \delta(t_0)]^T$ is the propulsion system feedback, and $[\beta_w(t_0), V_w(t_0)]^T$ refers to the wind conditions. The reference model is characterized by similar hydrodynamic properties and therefore acceptable model dispersion is within expectation. On top of the preliminary model, the data-driven NN calibrator (bottom green box) is built to map the rough dynamics to a surrogate model that is able to accurately predict ship behaviours. It is believed that the preliminaries of the ship dynamics are carried forward into the data-driven model by means of informative input.

Fig. 2 displays an explanation of the calibration process in this case. Assuming that at time t_0, the vessel is located at P_0 position in the north-east-down (NED) frame. The reference mathematical model propagates forward in time from here, and the indicated trajectory is shown as the red dashed line. $\hat{P}_1, \hat{P}_2, ..., \hat{P}_n$ refer to the model generated ship positions at time instance $t_1, t_2, ..., t_n$, and corresponding ship actual locations are registered as $P_1, P_2, ..., P_n$. In the local coordinate originating at $P_0(O')$, the model predicted position $\vec{m}_n$ is diverging from the actual position vector $\vec{r}_n$ with forecasting interval, represented by $\vec{d}_n$. The NN model is designed to learn the mapping relationship $f : \vec{m}_n \mapsto \vec{r}_n, \vec{m}_n = g(X)$ under supervision. The predictive outputs are thus $\vec{h}_n = f(X, \vec{m}_n)$. Owing to the approximating ability of the NN, the representative model is expected to respond correctly and predict accurately. By this method, the ship trajectory forecasting is implemented with a limited need for data and without the strict requirement of a precise ship dynamic model.

TABLE I: Main dimensions of the vessel before and after elongation.

Description	Parameter	Before elongation	After elongation
Length over all	$L_{oa}(m)$	31.25	36.25
Length between perpendiculars	$L_{pp}(m)$	28.9	33.9
Mass of vessel	$M(t)$	401.8	493.5
Breadth middle	$B_m(m)$	9.6	9.6
Draught	$d_m(m)$	2.6	2.6

B. Reference model

In the following, we will introduce the preliminary model groundwork. The R/V Gunnerus launched to sea in 2006, acts as the experimental platform. It has operated a variety of research activities within marine biology, archaeology, oceanography, sub-sea geology, fisheries, and marine technology [21]. The vessel is equipped with two permanent magnet-driven azimuth thrusters and one tunnel thruster from Brunvoll. Originally it was a ship of 31.25m and later was elongated to 36.25m in 2019. All characteristics except the length dimensions remained the same. The main physical dimensions of the two versions of R/V Gunnerus are listed in Table I. The vessel model of the short version is well established and verified, but the elongated version is not. However, due to the high similarity between them, it is reasonable to take the well-verified dynamic model of the vessel before elongation as the best available simulation model to construct the prior model groundwork. The reference model describes relations between actuators, external environmental disturbances, and the hull through the maneuvering model [22]. It is briefly reviewed here, and the simplifications are introduced as well. The ship kinematic model is expressed as:

$$\dot{\eta} = R(\psi)\nu \tag{2}$$

where $\eta = [x, y, \psi]^T$ is the ship position vector containing the north, east positions and yaw angle in the earth-fixed frame. $\nu = [u, v, r]^T$ is the ship velocity vector in surge, sway, and yaw directions respectively. $R(\psi)$ is the horizontal plane rotation matrix given as:

$$R(\psi) = \begin{bmatrix} cos(\psi) & -sin(\psi) & 0 \\ sin(\psi) & cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

The dynamic model considering the forces due to propellers, inertia, hull friction, winds, and waves is expressed as:

$$M\dot{\nu} + C_{RB}(\nu)\nu + C_A(\nu_r)\nu_r + D(\nu_r) = \tau_c + \tau_{wind} + \tau_{wave} \tag{4}$$

where $M \in R^{3\times3}$ is the vessel inertia matrix including added mass; $C_{RB}(\nu) \in R^{3\times3}$ and $C_A(\nu_r) \in R^{3\times3}$ are the skew-symmetric Coriolis and centripetal matrices of the rigid body and the added mass; $D(\nu_r) \in R^3$ is the damping vector, including linear and nonlinear terms which are a function of the relative velocity ν_r between the vessel and the current. $\tau_c \in R^3$ is the control vector consisting of forces and moments produced by the thruster system; τ_{wind} and τ_{wave} are the environmental load vectors of wind and waves, respectively. Given the measurement limitations of ocean currents and waves, and the desire to reduce modeling efforts, two simplifications are adopted:

- The forces due to ocean current are not constituted. Therefore, the ship velocity ν_r relative to the water will be replaced by ν in (4).
- The forces due to waves are not constituted. Therefore, the wave forces τ_{wave} will not be estimated in (4).

The wind force is the only environmental disturbance that can be estimated based on the wind speed and velocity measured on board. The deterministic model to estimate wind forces is given in (5).

$$\tau_w = \frac{1}{2}\rho_a V_{rw}^2 \begin{bmatrix} C_X(\gamma_{rw})A_{FW} \\ C_Y(\gamma_{rw})A_{LW} \\ C_N(\gamma_{rw})A_{LW}L_{oa} \end{bmatrix} \tag{5}$$

The relative wind speed is defined as $V_{rw} = \sqrt{u_{rw}^2 + v_{rw}^2}$ and attack angle $\gamma_{rw} = -atan2(v_{rw}, u_{rw})$, where $u_{rw} = u - V_w \cos(\beta_w - \psi)$, and $v_{rw} = v - V_w \sin(\beta_w - \psi)$. V_w and β_w represent the wind speed and its direction, respectively. C_X,C_Y, and C_N are wind coefficients specific for the hull or superstructure shape. A_{FW} and A_{LW} are frontal and lateral projected areas and L_{oa} is the overall length of the ship.

The propeller thrust T and torque Q are generally formulated as a function of shaft speed n in revolution-per-minute, time-varying states x_p, and fixed thruster parameters θ_p [23]. The thruster models (6) are generic models parameterized to fit Gunnerus.

$$\begin{aligned} T &= f_T(n, x_p, \theta_p) \\ Q &= f_Q(n, x_p, \theta_p) \end{aligned} \tag{6}$$

The actuator forces and moments are translated to the control forces and moments in horizontal plane by:

$$\tau_c = T(\delta)F_T \tag{7}$$

where δ is the thruster orientation vector, and $T(\delta)$ is the thrust configuration matrix shown next, which describes the geometrical locations of the thrusters. $\tau_c = [\tau_x, \tau_y, \tau_n]^T$ refers to the control force vector acting on the vessel; $F_T = [T_t, T_p, T_s]^T$ represents forces vector produced by tunnel thruster, port main thruster and starboard main thruster, respectively.

$$T(\delta) = \begin{bmatrix} 0 & \cos(\delta_p) & \cos(\delta_s) \\ 1 & \sin(\delta_p) & \sin(\delta_s) \\ L_{tx} & L_{px}\sin(\delta_p) - L_{py}\cos(\delta_p) & L_{sx}\sin(\delta_s) - L_{sy}\cos(\delta_s) \end{bmatrix}$$

where L_{tx}, L_{px}, L_{sx} are the distance along the longitudinal axis of the vessel from the vessel center of gravity to the tunnel thruster, port main thruster, and starboard main thruster, respectively. Similarly, L_{py}, L_{sy} are the distances along the lateral axis of the vessel. δ_p, δ_s are azimuth angles of port and starboard main thrusters.

The preliminary dynamic model of the elongated vessel is created and validated in Section IV-A2.

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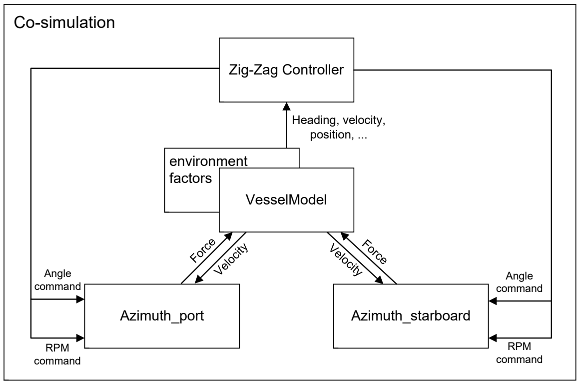

Fig. 3: Diagram showing the relationship of components in co-simulation of executing zigzag maneuver.

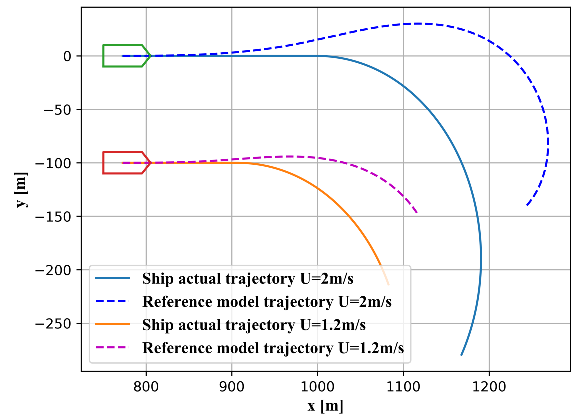

Fig. 4: Preliminary mathematical model validation.

TABLE II: Descriptions of sea states.

Beaufort scale	Wind velocity (m/s)	Wave height (m)	Current velocity (m/s)
Calm	0	0	0
Gentle	4	1	0.2
Moderate	8	2	0.2

C. Neural network calibrator

Among many existing data-driven methods, the neural network appears to be a good choice due to its simple structure and powerful approximation ability. A fully connected feed-forward NN model is then applied as a calibrator in this paper. The training of the network acts as a minimizing process where the weights of each neuron in the network are systematically adjusted in a manner that reduces the error between the NN output and the desired output. Three hidden layers are specified in the network architecture and each hidden layer contains ten neurons.

The input features include prediction time ahead of the current instance, the model predicted vessel velocities and positions in the horizontal plane, propulsion feedback, and external environment factors. Supposing prediction starts at t_0, the corresponding input vector and desired output will be expressed as:

- Input:$[t_i, \hat{\nu}_m(t_0+t_i|t_0), \hat{\eta}_m(t_0+t_i|t_0), RPM(t_0), \delta(t_0), \beta_w(t_0), V_w(t_0)]$
- Output: $\hat{\eta}(t_0+t_i|t_0)$

where $t_i \in [t_0, t_0+t_h]$ is the forward time interval, $\hat{\eta}_m(t_0+t_i|t_0)$ represents the reference model predicted positions starting from t_0, indicated by $\vec{m}_i$ in Fig. 2. $RPM(t_0), \delta(t_0), \beta_w(t_0)$, and $V_w(t_0)$ are sensor data recorded at t_0.

The other settings to instantiate the network are presented here. The activation function for the hidden layer is ReLu and Adam is selected as the optimizer with a learning rate of 1×10^{-3} to update weights. Each input measurement in the training set is normalized with a standard scalar and the corresponding normalization statistics are applied to the test set. All the experiments conducted used the same hyper-parameters and training algorithm setting. In simulation, the data set in total includes 70 sequences, each of which has 600 samples and a sampling frequency of 20Hz. In sea trials, motion data are sampled at 1Hz. They were randomly split into 70%, for training sets, and 30% for testing sets. The training set evaluated the performance by minimizing the mean square error (MSE) metric between desired values and regressed values. The proposed network is implemented by using Scikit-learn in Python.

IV. Experiment Results

To verify the effectiveness of the proposed hybrid cooperative model, experiments in both simulator and open sea are conducted. The experiment setup and results will be discussed in this section.

A. Simulation studies

1) Simulation setup: The simulation experiments are conducted in Vico, a generic co-simulation framework based on the Entity-Component-System software architecture that supports the Functional Mock-up Interface (FMI) as well as the System Structure and Parameterization standards [24]. The user may manipulate the wind, waves, and ocean currents to mimic environmental conditions. The co-simulation setup for a zigzag maneuvering experiment is presented in Fig. 3, and each block represents an FMI-compatible model. The environmental conditions are specified as initial values for the elongated *VesselModel*. The zigzag controller is developed by the author, and the azimuth model is supplied by the thrust manufacturer.

To validate the stability and robustness of the proposed method, three different sea states are simulated as shown in Table II. The wind, wave, and current come from the same direction. Data of ship motion are sampled when the ship executes multiple zigzag maneuvers in the simulator, with the azimuth angle varying in the range of $[10, 20, 30]$ degrees, the same as the heading turn over range.

2) Reference model validation: The preliminary model fidelity against the truth ship is verified in Fig. 4. The elongated ship and the reference mathematical model are simultaneously actuated in calm water by the same commands. As can be seen, when the ship is moving forward, the model output trajectory is highly close to the ship actual positions. The resemblance is implied by the similar ship hulls and identical thruster.

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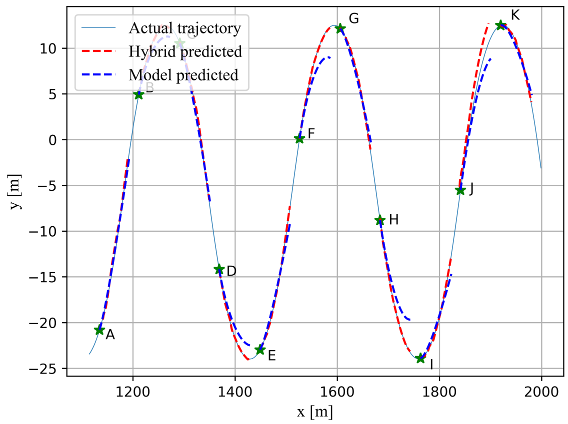
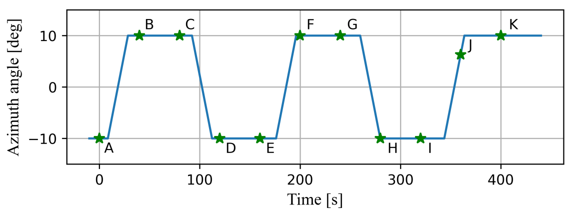


(a) Predicted ship positions of model-based and hybrid approach



(b) corresponding azimuth angle when prediction starts

Fig. 5: Results of performing model-based and hybrid predictions in calm water.

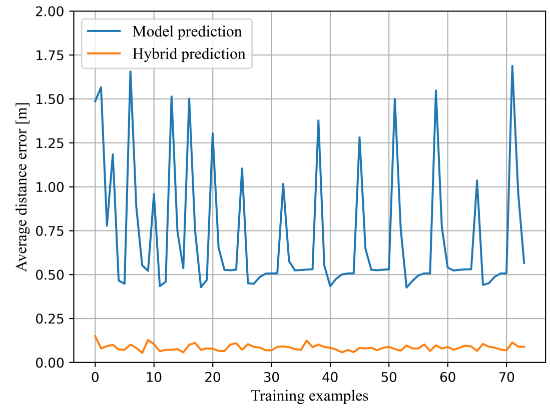


Fig. 6: The average distance errors of two approaches.

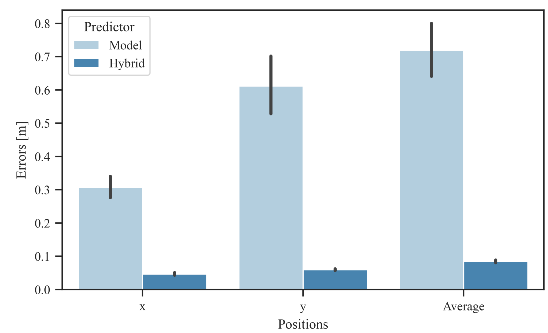


Fig. 7: The prediction errors of reference model and hybrid approach in different directions.

However, when the ship is turning at $10°$, the variations between the two models grow considerably, and the larger a ship's forward speed, the more extensive divergence. This inconsistency in turning maneuverability may be due to the changing inertial effects because of the elongation.

In general, the results are consistent with the hypothesis outlined in Section. III-B that the preliminary reference model has fidelity to preserve the domain knowledge to an extent but is not credible enough to represent the new ship. Except for the systematic errors inherited from the reference model as shown in this figure, the undefined uncertainties and stochastic environmental disturbances will also lead to great distortion of the model trajectory. The proposed hybrid modeling approach is therefore designed to make up this problem and pursue an accurate representative model of the elongated version of R/V Gunnerus.

3) Simulation experiment results: To evaluate the predictive model performance, the following metrics are applied:

- Mean absolute error (MAE) (8) for evaluating errors in north and east directions.
- Average distance error (9) for evaluating mean variation from actual location.

$$MAE = \frac{1}{N}\sum_{1}^{N}|\hat{x}_i - x_i| \tag{8}$$

$$e_{ave} = \frac{1}{N}\sum_{1}^{N}\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2} \tag{9}$$

where N refers to the sample number.

By performing both reference model prediction and hybrid method, we obtain the forecasting performance of 30 seconds in the future during the zigzag maneuver in calm water, as shown in Fig. 5a. The green star marks the start position of each prediction. The corresponding azimuth turning angle is presented in Fig. 5b. In this figure, it is shown that the hybrid approach calibrates the turning maneuverability of the reference model as the prediction horizon grows. The slight discrepancies observed at trace J are caused by the fact that the control command is transiting when prediction starts, and such sequences are originally not covered in the training data. In that case, the calibration performance might be somewhat degraded.

TABLE III: Evaluation of prediction errors of reference model and hybrid approach at different sea states.

Sea states	Positions	Prediction errors		
		Model	Hybrid	Reduction
Calm water	x	0.31	0.05	84.8%
	y	0.61	0.06	90.3%
	average	0.72	0.08	88.3%
Gentle	x	1.19	0.18	84.9%
	y	1.61	0.06	96.3%
	average	2.19	0.20	91.0%
Moderate	x	3.02	0.36	88.1%
	y	1.56	0.10	93.6%
	average	3.60	0.39	89.2%

Fig. 6 shows the variation of average error of both approaches with respect to each training example. It indicates that the hybrid method works well on decreasing errors and

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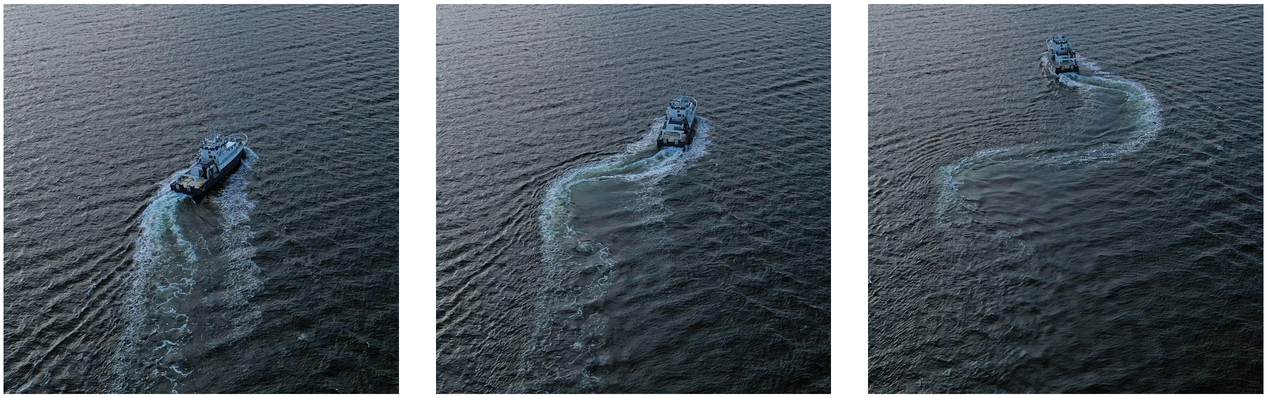

Fig. 8: R/V Gunnerus when executing a zigzag maneuver on site in Trondheim, Norway.

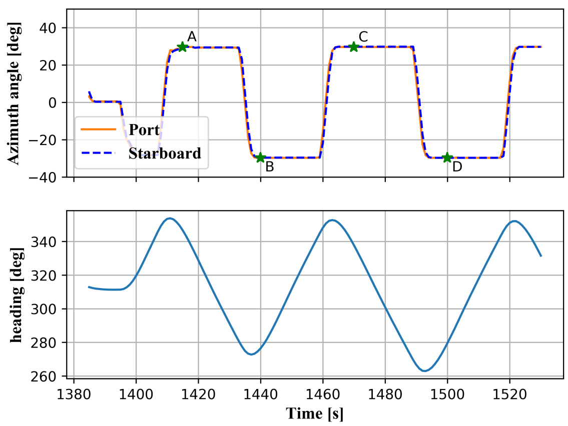

Fig. 9: Azimuth turning angle and ship heading during maneuvering.

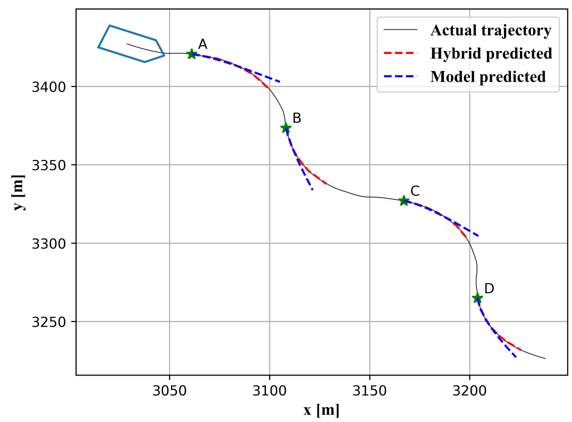

Fig. 10: Hybrid predictions in comparison with model predictions in real life.

improving prediction accuracy. In Fig. 7, the distributions of each error index are presented. On average, the hybrid predictor decreases the prediction errors to a significant extent, inducing a high-fidelity representative model of the elongated vessel. Particularly, a more noticeable calibration performance of y direction is observed compared to that of x direction.

The experiment results under different sea states are listed in Table III. From the table, the hybrid modeling method is found a significant decrease on the prediction errors. An increasing error reduction in the x position is addressed when the sea state gets severe. It is observed that the integration of the NN calibrator works well on improving the forecasting accuracy concerning various environments, demonstrating robustness.

B. Full-scale trials

The maneuvering experiment of elongated R/V Gunnerus was conducted in November 2019 in Trondheim, Norway. Fig. 8 shows successive movements when the ship was executing a zigzag in the open sea. During this process, thirteen sensor channels related to the ship motion of the vessel were sampled, including:

1) *Position:* the linear position measurements given in the NED frame and angular position heading angle of the ship.
2) *Velocity:* the linear surge velocity, linear sway velocity and angular yaw rate.
3) *Environment:* global wind direction and global wind speed measurements.
4) *Command:* port thruster RPM and angle, starboard thruster RPM and angle, as well as tunnel thruster RPM.

During maneuvering, the thruster turning angle and ship heading are changing, as shown in Fig. 9. In this process, the tunnel thruster is turned off. By integrating the sampled signals in the current instance as well as the preliminary mathematical model outputs into the neural network, the desired positions at the next instance are obtained. The prediction interval is 15 seconds, and the calibration results are verified as shown in Fig. 10. It is viewed that the hybrid predictions have a satisfactory agreement with the actual ship trajectory compared with those propagated by the reference mathematical model. The hybrid predictive model is proven effective and can be applied in realistic ocean scenarios. Note that the training data can only be sampled when the thruster orientation is sustained in the prediction interval, so the forecasting interval is shorter in real-life experiments.

C. Discussion

The findings of this study support that the hybrid methodology, based on a coarse simulation model and a data-calibrator, has significant potential to improve ship prediction accuracy during maneuvering. In particular, the integration of the NN model handles the stochastic environmental effects in a significant way. The hybrid modeling method overcomes the respective systematic errors inherited from the reference model while avoiding the modeling difficulties of complex environment configurations. Therefore it should be better suited for situations where high sea states are accounted for compared to mild conditions.

Moreover, to ensure safe maneuvering in constrained areas such as canals or rivers, the conventional model-based predictor is usually not qualified. As known, the environmental conditions of such situations are unpredictable, and the complex hydrodynamic interaction leads to a considerable increase in resistance when entering such areas. Meanwhile, the probability that one ship reacting to avoid collisions with multiple ships is expected to increase in busy waterway. Developing a high-level autonomous vessel that can operate in such unpredictable environments is practically delicate. Facing these challenges, the synergy of model-based and data-driven approaches is enabled to improve predictive performance and deliver accurate results. A promising future of the hybrid methodology in the real ship maneuvering safety and multi-ship interaction is expected by the authors.

This hybrid modeling frame incorporates the dynamic model into the data-driven model as additional input and calibrates the model in principle. It differs from the direct addition of two domain models, which is designed to correct a model's bias from the phenomenon view. Therefore, the model foundation plays an even more critical role in this method. It will determine how much needs to be reinforced and how much confident information it provides to the data calibrator. The criteria for selecting the candidate preliminary model is not deeply discussed in this paper, and future research should give it much more attention. Theoretically, there is one threshold of reference model fidelity. When the preliminary model fails to capture the system properties, it cannot be employed as model groundwork. Clarifying the boundaries of this method is quite significant as it could loosen the requirement on the deterministic model.

There are also concerns about the data calibrator. Incorporating an informative input from the preliminary model is desirable to moderate the strict requirement for data variation compared to pure black-box models. As a data-based algorithm, however, it cannot bypass the general drawback in extrapolation capabilities. One way expected to address this is to develop novel algorithms, for example, back-propagation over time. More future efforts should be paid to exploring better calibrators.

V. Conclusion

In this paper, a novel model-data-hybrid prediction modeling method for actual ship motion prediction is proposed and investigated. The hybrid model is created based on the best available dynamic simulation and designed to improve the fidelity and predictive capability of a partially accessible model. With the preliminary model serving as the reference, the data-driven NN is verified to be capable of calibrating the coarse model and providing accurate ship position predictions in 30 seconds during zigzag maneuvering. In the simulation cases, the proposed model decreased around 90% of the average distance errors in varying sea states, proving robust and stable. Verification results of full-scale trials show that the model offers satisfactory forecasting performance in realistic ocean conditions. Ultimately, the hybrid model integrates the strengths of domain knowledge and data, providing a novel way of improving the prediction accuracy as well as reducing the modeling efforts and implicitness.

As discussed, this method relies on both a numerical model and a data model. The effect of coupling between two modules on the method's integral performance needs further investigation. Besides, the fidelity and sensitivity of the reference model are supposed to influence the features of the data model, and on the other hand, to what extent the data-driven model can reinforce the approximate model also relies on the predetermined knowledge. Hence, more research will be conducted on the hybrid structure and coupling effects between components in the future. Following the steps towards automation in the marine industry, the hybrid modeling methodology is expectedly compatible with complicated maneuver situations. Thus, the ensuing research upon the hybrid model like the motion planning, as well as collision avoidance, will be added to the future picture.

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