

An Efficient Recurrent Neural Network for Dead Reckoning of Dynamically Positioned Ships

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Abstract—When a ship experiences a loss of position reference systems, the ship’s navigation system typically enters a mode known as dead reckoning to maintain an estimate of the position of the ship. Commercial systems perform this task using a state estimator that includes mathematical model knowledge. Such a model is non-trivial to derive and needs tuning if the dynamic properties of the vessel change. To this end we propose to use machine learning to estimate the horizontal velocity of the vessel without the help of position, velocity or acceleration sensors. A simulation study was conducted to show the ability to maintain position estimates during a Global Navigation Satellite System outage. Comparable performance is seen relative to the established Kalman Filter model-based approach.

Index Terms—Dead reckoning, ship motion prediction, Kalman filter, feedforward/recurrent neural network, input selection.

I. INTRODUCTION

SYSTEM failures that occur during the performance of operations at sea that impose strict constraints on the ability of a ship to maintain position may have severe consequences. In order to mitigate the risk of failures, ships used in such operations have redundant systems. As marine operations grow increasingly autonomous and remotely operated [1], the importance of redundant systems to aid in controlling the vessel in case of failures increases. Failures that occur when a vessel is operating autonomously must be handled in a timely fashion through the issuance of a warning to a remote operator. In cases of a loss of absolute position measurements, a ship normally enters a mode known as dead reckoning (DR) to provide estimates of the vessel position without the use of external signals. Various strategies exist to provide such estimates, but the general approach is to propagate the velocity and course of the vessel from a known position [2].

With regards to the position reference used by, for example, stationkeeping motion controllers, various sensory platforms measuring the absolute or relative position may be applied, such as differential Global Navigation Satellite System (dGNSS) or radar or hydroacoustic systems [3]. While hydroacoustic-inertial navigation systems offer positioning solutions of similar quality to GNSS-inertial navigation systems, they rely on deployed seabed transponders [4]. Depending on the type of operation, this might not be a feasible strategy. The most generic and available system is therefore the dGNSS.

As positioning systems normally use signals from satellites to calculate position, there is a potential to experience both a communication dropout between the remote operator and the autonomous vessel, as well as a loss of the GNSS position

reference signals. In such a case, the accuracy and long-term performance of the DR system becomes important in order to maintain an accurate estimate of the current position of the vessel.

In commercial navigation systems the Kalman Filter (KF) is often used to filter the wave-induced motion and provide estimates of the vessel velocity [5], [6]. At a minimum, position and heading measurements are input to the estimator. These measurements are combined with the linearized vessel model to provide the state estimates. Wave-filtering ensures that the oscillatory wave-induced motion does not enter the controller of the vessel causing increased fuel consumption and actuator wear [7]. The widespread use of KFs for state estimation and wave filtering makes it a natural choice as a tool for providing DR position estimates as well.

Nonlinear observers that do not require knowledge of the vessel model have also been proposed for marine vessels operating in stationkeeping mode, often referred to as Dynamic Positioning (DP). Bryne, Fossen and Johansen performed wave filtering based on the Inertial Navigation System (INS) output [8], while Rogne et al. used Inertial Measurement Unit (IMU) data for DR [9]. The difference being that the IMU provides the raw angular velocity and specific force measurements, while the INS integrates these measurements into a navigation solution in terms of a position, velocity and attitude.

In the event of a dGNSS position reference failure, the state estimator, assuming the KF is used, can make estimates based only on the vessel model [5]. The position reference failure may be caused by external factors such as loss of a direct line of sight between satellite and receiver, intentional signal modification by a third party, or severe signal degradation due to noise incurred along the signal path [10]. Vessel model inaccuracies cause the position estimate to diverge from the real vessel position over time. If nonlinear observers and IMU data for DR are used, the integration of velocity and acceleration measurements that contain errors cause the estimated position to diverge from the true position. Typical error sources of IMU sensors are bias, misalignment relative to the vessel frame axes and temperature variation [11].

In this paper we design a data-based method for DR that involves modelling the horizontal velocity of the vessel in terms of inputs like thruster command/feedback values, thruster power consumption, measurable environmental states, and heading. A Long Short-Term Memory (LSTM) neural network was used for this purpose due to its ability to handle large time delays between input data and the resulting effect

on the output data.

As the heading of the vessel may be measured by an internal sensor system such as the compass, availability of the heading measurement is independent of the GNSS system. Thus the change in position may be calculated from the heading angle, the predicted body-fixed velocity at the next time step, and the sampling time. Adding this to the position derived at the previous time step results in the estimated DR position at the next time step. Figure 1 shows a schematic view of the general units required. Under normal operation the "Velocity" unit provides target values for the supervised training. The target values have corresponding input vectors lagged by one sample step and consist of variables related to the actuators of the vessel, wind conditions and the vessel heading. The "Initial learning" block performs offline training based on the sampled targets and inputs. If a GNSS failure occurs, no targets are available, which precludes any further supervised training. At this point the input vector is used to form one-step predictions of the longitudinal (surge) and lateral (sway) velocity of the vessel. The proposed method

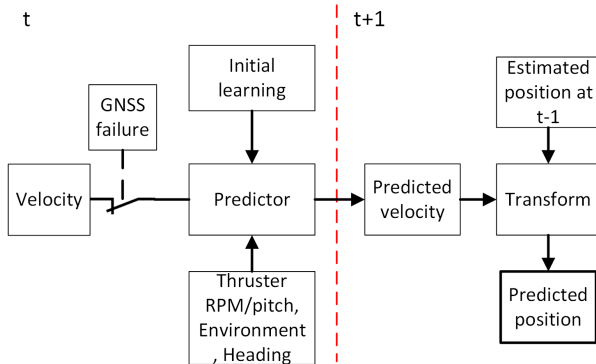


Fig. 1. The proposed approach for performing DR using machine learning methods.

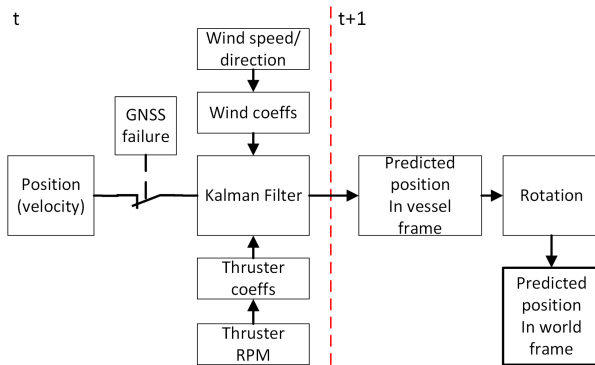


Fig. 2. The approach for performing DR using the KF.

has the advantage of not being dependent on a mathematical model of the vessel. Thus it offers a more generic way of representing the velocity/position of a vessel due to force input by thrusters and other relevant and obtainable measurements. In addition, automatic parameter adaptation can be performed purely based on sampled data. This may be relevant if, for

example, the load distribution on the hull changes during operation. On the other hand, state estimators, such as the KF and nonlinear observers, allow for proof of stability, as well as a more transparent input/output relationship. Figure 2 shows how the KF approach to DR may be performed. For both figure 1 and figure 2 the vertical red line marks the line between measured position signals and predicted position signals. A comparison in terms of position estimation performance was made between the two methods to gauge the feasibility of the LSTM model for DR.

The remainder of this paper is organized as follows. Section II reviews related literature. Section III introduces the model used for predicting the vessel motion, how it is configured in terms of input, architecture and hyperparameters and also the signals generated by the vessel simulator. Results from two case studies, along with a description of the simulated vessel and the environmental disturbances imparted on it, are given in Section IV. Section V provides a discussion on the results from Section IV and Section VI offers a conclusion on the performance and validity of the proposed method.

II. RELATED WORK

The DR mode is a position reference fallback system for marine surface vessels. Vessels operating beneath the ocean surface may apply DR positioning techniques as the primary system of determining position [12]. German et al. compared two methods of determining position for an Autonomous Underwater Vehicle [13]. Internal sensors included a three-axis magnetic compass, a Doppler Velocity Log and a depth sensor. The first method relied on an Extended Kalman Filter fusing Global Positioning System (GPS) data, transferred acoustically from an autonomous tender vessel, with the onboard sampled data. The second used only the internal sensors, which produced dead-reckoned position solutions.

For DR of ocean surface vessels, Diamant and Jin used a three-axis accelerometer to provide the dead-reckoned heading and position of a vessel [14]. They used machine learning to classify accelerometer data into bins of similar pitch angle and then project it onto the local north-east horizontal plane. The projected accelerations were integrated to yield the estimated position and heading. The motivation for using only a three-axis accelerometer as sensor input for DR was to avoid using measurements from a gyrocompass. According to the authors this sensor may be unavailable or contain too much noise to be of use in estimating the attitude of the vessel.

Rogne et al. investigated the DR capabilities of an INS aided by dGNSS signals [9]. They applied two different low-cost IMUs, providing accelerometer, compass, and angular velocity measurements. Two different nonlinear observers were compared, using no information about the vessel model, on a test set sampled on a vessel performing a DP operation in the North Sea. They found that the top performer had a position error, after 10 minutes of dGNSS outage, of about 100 m.

DR has been used in other domains as well, such as the automobile and aerospace. When comparing seagoing vessels with airplanes, it is clear that there is a large difference in

dynamic properties and how severe the impact of wind is on the frame of the respective objects. This is especially true for Unmanned Aerial Vehicles (UAVs) due to their small size. Mokhtarzadeh and Gebre-Egziabher performed a study on cooperative navigation for UAVs [15]. Several UAVs, connected in a network, shared navigational information during a 5 minute GPS outage to reduce the position error drift rate of a DR based navigation filter. The authors opted to use an integration of airspeed measurements, instead of the more traditional INS sensors in order to avoid the double integration necessary to determine position from the acceleration estimated by the INS. An additional advantage to this approach is the separation of the DR operation from the Attitude and Heading Reference System. Instead of using an airspeed sensor Fusini, Johansen, and Fossen used a downward-looking camera and a machine vision system to provide the velocity of the UAV [16]. The acquired velocity was input to both a nonlinear observer and an exogenous KF for performing DR, in which a bounded error rate was achieved during experimental real-system testing.

Land vehicles usually follow predefined tracks, often in areas that are not conducive for robust GNSS signal reception. To produce continuous in-car navigation services, DR/INS systems, digital maps and mathematical models of the vehicle typically complement the GNSS measurements. Skog and Händel provide an overview of such systems, and the methods used for fusing both external sensor data (e.g. GNSS) and internal sensor data (e.g. odometer, gyroscopes, and accelerometers) [17].

Abbott and Powell provided a study of the error contribution of various sensors for an in-car navigation system [18]. They applied sensitivity analysis to gauge the performance of a KF sensor fusion algorithm against a reference system. Their findings suggested that the use of differential GPS (dGPS) offered improved calibration of the internal sensors, resulting in significant reduction of error drift during a satellite system outage. Thereby, relatively inexpensive internal sensors combined with dGPS could provide sufficiently accurate DR systems. Extending the flexibility of the KF for combining data from several sensors at various sampling rates, Barrios, Motai, and Huston introduced a dynamic state noise covariance matrix [19]. The purpose of this dynamic matrix is to reflect the state uncertainty more accurately when sensors drop out for any length of time.

Like Rogne et al. [9], Ahmed and Tahir [20] recognize that high-performance IMU units contribute significantly to the overall system cost. That motivated the use of a low-cost Micro Electro-Mechanical System IMU unit, containing a tri-axial gyroscope and accelerometer, to accurately determine the attitude of a car. They estimated the vehicle acceleration by using the kinematic vehicle model and the known norm of the gravity. In addition to providing accurate attitude estimates, the ability to separate the gravity-induced acceleration components from the overall acceleration measurement proved beneficial to DR performance.

III. METHODOLOGY

In this section we introduce the measured signals, delays present in the actuators of the simulated vessel and the LSTM network model. Methods of limiting the input data dimension and selection of LSTM hyperparameters are also considered.

A. Measurement noise

Noise was added to the following measured states.

- Position: The position measurements given in the North East Down (NED) frame.
- Heading: Rotation about the z-axis of the vessel.
- Velocity: The linear velocity given in the NED frame.

The position and heading measurements, as seen by the consumers of the sensor data, are, then, a sum of the true value sampled from the simulator, white noise, a bias, and a Gauss-Markov (GM) process. Equation 1 shows the discretized GM process:

$$x[k+1] = \exp\left(-\frac{\Delta t}{T_c}\right)x[k] + \sigma w[k] \quad (1)$$

where k is the discrete time variable, Δt is the sampling interval, T_c is the correlation time, and w is the Gaussian white noise with a standard deviation of σ . Equations 2 and 3 show the addition of noise terms to form the expression for the position and heading with noise [21]:

$$\mathbf{p}[k] = \mathbf{p}_{true}[k] + \mathbf{x}_p[k] + \boldsymbol{\sigma}_p \mathbf{w}_1[k] + \boldsymbol{\mu}_p \quad (2)$$

\mathbf{p} is a two-dimensional column vector containing the north and east position with additive noise, \mathbf{p}_{true} is the noiseless north/east position, \mathbf{x}_p holds the corresponding GM processes for the two components, $\boldsymbol{\sigma}_p$ is a diagonal matrix containing standard deviations of added white noise (\mathbf{w}_1) and $\boldsymbol{\mu}_p$ holds the position bias.

$$\psi[k] = \psi_{true}[k] + x_\psi[k] + \sigma_\psi w_2[k] + \mu_\psi \quad (3)$$

Noise added to the heading signal is described in Equation 3, where ψ is the heading angle containing noise, ψ_{true} is the noiseless heading angle, x_ψ is the GM process related to the heading angle, σ_ψ is the standard deviation of the Gaussian white noise w_2 and μ_ψ is the heading angle bias. Table I shows the parameters used in simulating the position and heading states with noise. The angular/linear velocity received only a constant bias and white noise [22].

TABLE I
PARAMETERS USED FOR THE ADDITIVE NOISE ELEMENTS OF THE POSITION AND HEADING MEASUREMENTS.

	GM σ	T_c	White noise σ	Bias μ
Position	0.1 m	240 s	0.2 m	[-0.2,0.2] m
Heading	0.1 °	60 s	0.1 °	[-0.1,0.1] °

B. Time delay

Delays in time between a change in thruster command (input) and the given response in velocity (output) are present in the sampled time series. They are caused by both the linear/rotational inertia of the vessel and the rotational inertia of the various thruster systems. Figure 3 shows the surge velocity response due to a step increase of 5 degrees in the commanded pitch angle of the two main thrusters. At a pitch angle of 5 degrees the thrusters output about 5 % of the maximum thrust force. We see that the rate of change of the thruster itself is limited to 1.4 degrees per second, such that it takes approximately 3.5 s to reach 5 degrees. Furthermore, the time spent to reach a surge velocity of 63 % of the steady state value of 0.37 m s^{-1} is 50 s.

During normal DP operation there will be no step function inputs as the controller reaches a relatively fixed command vector to compensate for the external disturbances. However, perturbations in thruster commands occur due to imperfect wave filtering, causing setpoint changes in the range $[-0.5, 0.5]$ degrees. To ensure that the input vector to the machine learning algorithms contain information of the most significant transient effects, due to changes in thruster commands, we include 10 seconds of history data for each input variable. Similar delays are seen for the tunnel thrusters. Delays also exist between the vessel velocity and the changes in wind velocity and direction.

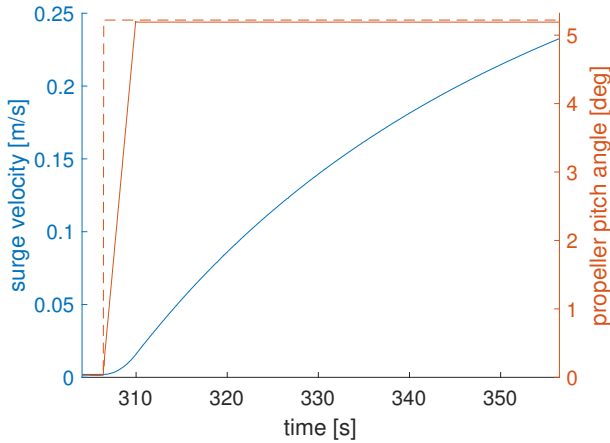


Fig. 3. The delayed response of the two variables surge velocity (solid blue) and actual thruster pitch angle (solid red) as a reaction to a step increase in the commanded thruster pitch angle (dashed red).

C. Position estimation concept

Two networks predict the horizontal velocity components of the vessel: one that predicts the surge velocity and one that predicts the sway velocity. This makes it possible to provide a custom network in terms of input pattern for each of the velocities expressed relative to the horizontal axes of the vessel frame of reference. After an initial network learning phase the proposed approach does not rely on samples produced by a GNSS system. Inputs to the networks are therefore available up to, and including, the discrete step k .

This enables a prediction of the velocities at the subsequent time step, $k+1$. To get from a predicted velocity to a predicted travelled distance in the NED frame, the predicted velocity is multiplied by the sampling time and rotated according to the heading angle. At this point the travelled distance due to the predicted velocity, Δp in Figure 4, is added to the previously estimated position. Equation 4 gives the equation for the propagation of position

$$\hat{p}[k+1] = \hat{p}[k] + \mathbf{R}(\psi)\hat{v}[k+1]\Delta t \quad (4)$$

where \hat{p} is the estimated north/east position of the vessel in the NED frame, \hat{v} is the predicted velocity vector relative to the vessel frame coordinate system, and $\mathbf{R}(\psi)$ is the square rotation matrix that transforms the predicted velocities to NED-frame velocities. \hat{v} contains the surge and sway velocity of the vessel, variables $(\hat{v}_{lon}, \hat{v}_{lat})$ of Figure 4). k is the discrete step index with a step interval of $\Delta t = t[k] - t[k-1]$. A visualization of the process is given in Figure 4. At time $t[k]$ the horizontal position is measured using the signal received from GNSS satellites. At the next time step, $t[k+1]$, the receiver on the vessel fails to produce the position of the vessel via GNSS signals due to one of the aforementioned reasons for GNSS unavailability. At this point, the DR algorithm is activated and provides an estimate of the vessel position through the prediction of the surge (\hat{v}_{lon}) and sway (\hat{v}_{lat}) velocities seen in Figure 4. Together they make up the velocity vector $\hat{v}[k+1]$ of Equation 4. The

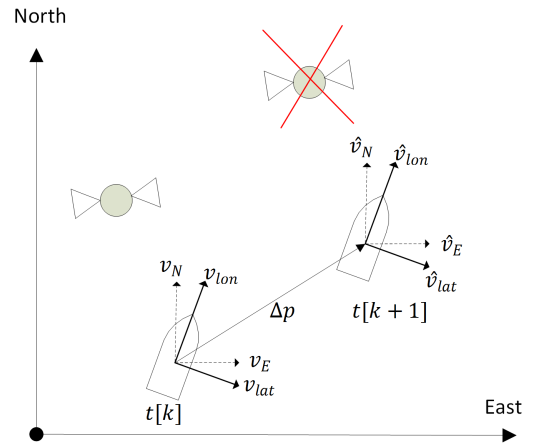


Fig. 4. A switch from normal operation ($t[k]$) to loss of GNSS system, requiring a DR system to estimate the position at the next step without an absolute position measurement.

method proposed in this paper, the LSTM recurrent neural network, by design only receives input variables that contain information about external disturbances, the heading angle, and the control intention of the vessel. Measurable external disturbances include the wind velocity and wind direction for the system used in this paper. Although systems exist for measuring and estimating the wave spectrum parameters in the vicinity of the vessel [23], [24] and measuring the velocity and direction of the ocean current affecting the hull [25], we limit the environmental sensory equipment to sensors that are currently available in the system. A key assumption at this stage is that the velocities relative to the vessel frame are

available without bias. If the velocity targets used for training the machine learning methods contain biases, the error rates during DR are increased significantly.

D. LSTM

A LSTM network was used to model how the velocity of the vessel relates to the aforementioned inputs. LSTM networks differ from feedforward networks in that they have weight connections between all nodes that are not input nodes [26]. To avoid the problem of vanishing/exploding gradients for backpropagation-through-time learning, Hochreiter and Schmidhuber devised a unit called a memory cell [27]. It contains a Constant Error Carousel (CEC) unit that aims to keep the error flow constant through a unity self-connection. A linear activation is used in the CEC. The memory cell contains two multiplicative gate units in addition to the CEC. They control the access of the input signals and output signals to the CEC. As LSTM networks are particularly well suited for learning the relationship between events that are separated by a long time delay, we include this network in our analysis. Due to the large inertia of both the vessel and the various actuator systems, there may be delays between such events as the inputting of a command and significant position change. See Section III-B for a visualization of the time lag. Functions in the Matlab Neural Network toolbox were used for training and prediction using the LSTM network.

As sensors output measurements of various physical quantities, they operate in different value ranges. In order to have each measured variable contribute equally as part of the input vector, all data should be normalized. In order to scale both the variation and the absolute value of each variable in the dataset, we use the mean/standard deviation approach to normalization according to Equation 5

$$\mathbf{x}' = (\mathbf{x} - \bar{\mathbf{x}})/\text{std}(\mathbf{x}) \quad (5)$$

where \mathbf{x} is the N-sample by M-variable training dataset, $\bar{\mathbf{x}}$ is the mean value of each variable, $\text{std}()$ represents the standard deviation of the variables and \mathbf{x}' is the normalized data. All of the signals used in this paper have a bounded range, meaning that given a representative set of training data, the range of the test data does not differ significantly.

E. Input selection

By limiting the number of input variables to those that hold a certain level of information about the output states, the network's ability to generalize increases and its complexity is reduced. Mutual Information (MI) is applied in this paper to facilitate the dimension reduction of the input vectors used by the machine learning models. This operation is known as input selection and is performed prior to generating, or updating, the actual predictive network. MI provides a measure of the reduction of uncertainty about a variable x given a variable y [28]. It is defined by

$$I[\mathbf{x}, \mathbf{y}] = - \int \int p(\mathbf{x}, \mathbf{y}) \ln \left(\frac{p(\mathbf{x})p(\mathbf{y})}{p(\mathbf{x}, \mathbf{y})} \right) d\mathbf{x}d\mathbf{y} \quad (6)$$

where $p(\mathbf{x})$ and $p(\mathbf{y})$ are the distributions of \mathbf{x} and \mathbf{y} , respectively, and $p(\mathbf{x}, \mathbf{y})$ is the joint distribution between the two sets. Thus, if the evaluation of $I[\mathbf{x}, \mathbf{y}_1]$ results in a larger numerical value compared to the evaluation of $I[\mathbf{x}, \mathbf{y}_2]$, the variable \mathbf{y}_1 contains more information than the variable \mathbf{y}_2 about the variable \mathbf{x} . Estimators are employed for practical implementations of MI and its use within the domain of time series regression is documented in [29] and [30]. In this paper we calculate MI using the Matlab functions presented in [31].

1) *Input structure*: The vessel has six thrusters: two bow tunnel thrusters, two stern tunnel thrusters, and two main thrusters with rudders. In this paper, the vessel performs stationkeeping using one Proportional Integral Derivative (PID) regulator per Degree of Freedom (DOF), preceding a basic thrust allocation unit that applies the unconstrained generalized inverse method for distributing motion controller force requests. To simplify the allocation problem, the rudder angle of the two main thrusters was fixed. A further simplification was performed to decouple the effect of the main thrusters on the rotation of the vessel. For all simulations in this paper the main thrusters were operated in unison, such that they only affected the motion of the vessel along its longitudinal axis. By intuition we select inputs to represent the velocity of the vessel in its forward and sideways axes, individually. The forward/surge speed varies depending on the inertia, thruster force, and environmental force applied along that axis. Thus, measurements of the main thrusters (fixed along the forward axis) are included along with the wind direction and velocity and heading angle. Without a mathematical model of the effect of the thruster commands and wind magnitude and direction, we aim to derive this from the measurements. We take a similar approach in selecting the input variables for the velocity in the sway direction, selecting measurements from both a forward- and a stern-mounted thruster as well as the heading and wind measurements. Equation 7 shows the partitioning of the variables in an input pattern,

$$\begin{aligned} \mathbf{z}_k = & [x_1[k] + x_1[k-d] + \dots + x_1[k-(n-1)d], \dots \\ & x_2[k] + x_2[k-d] + \dots + x_2[k-(n-1)d], \dots \\ & x_m[k] + x_m[k-d] + \dots + x_m[k-(n-1)d]] \quad (7) \end{aligned}$$

where \mathbf{z} marks the total, one-dimensional, input pattern, k is the discrete sample step, x is the measured input variable, d is the delay in number of steps, n is the number of delayed samples to include of a variable and m indicates the type of input variable. See the first column of Table III for a list of input variables used in the two separate input patterns, which corresponds to the variable m .

2) *Optimizing network structure*: Depending on parameters such as neuron number, layer depth, size of training dataset, etc., the evaluation of a single instantiated neural network may be quite costly in terms of computation time. The approach of Snoek, Larochelle, and Adams, termed Bayesian optimization, provides efficient hyperparameter optimization, thereby lowering the overall cost of producing an efficient model configuration [32]. In this paper the optimization of the LSTM network (see Section III-D) was focused around the number of LSTM blocks in a single layer, as well

TABLE II
THE DIMENSIONS OF THE SIMULATED VESSEL.

Description	Value
L_{pp}	82.7 m
Breadth	23.1 m
Displacement	10180×10^3 kg

as the learning rate, the two most important parameters according to [33]. A range of [10, 200] was selected for the number of blocks while a range of $[10^{-5}, 10^{-1}]$ was selected for the learning rate. The cost function returned the mean-squared-error (MSE) of the validation samples (10% of the total number of samples used for training), which provided a means of quantifying the expected performance of the network. Together with the input selection stage, the number of parameters in need of tuning has now been limited to that of setting the threshold for the input selection and the upper/lower values of the range in which to perform hyperparameter optimization.

IV. SIMULATION RESULTS

We propose to use a data-based model, described in Section III-D, to model the relationship between various inputs and the predicted linear, vessel-frame relative, velocities of the vessel at the next time step. To assess the performance and the validity of this method, we compare it to two other models:

- **KF:** Linearized equations of motion are obtained for the vessel by rotating the position measurements to a vessel-parallel coordinate system at each time step. This facilitates the use of a linear KF observer model for the DP test case in this paper [34].
- **SLFN:** A single-layer feedforward neural network, which represents the most basic structure among neural networks used for regression.

In the case of the KF we coast through the outage using the thruster command, wind velocity, and wind angle as input. These measurements are fed to the mathematical model of the vessel. The individually learned predictive models of the two machine learning methods replace the explicit vessel model. The machine learning DR methods do not use the vessel model or sensors for measuring the displacement of the vessel.

A. Vessel and environment description

All experiments were conducted in a commercial simulator developed by the Norwegian company Offshore Simulator Centre AS. It features a simulated environment in which a user may manipulate the wind, waves, and ocean current to mimic real-life conditions. It offers a library of virtual vessels to choose from. For these experiments, a multi-purpose offshore vessel was selected. Table II provides its main dimensions. Figure 5 shows a view of the simulated environment with the selected vessel engaged in a DP operation close to a static rig. For the specific simulation study performed in this paper, varying environmental parameters were applied. The direction of the environmental disturbances is incremented

at intervals of 30 degrees from 0 to 360 degrees, relative to the vessel frame. At each fixed direction a set of wind and wave magnitudes were applied consecutively, causing increasingly severe weather conditions. Table IV shows the wind and wave magnitude for each of the distinct conditions faced by the vessel at the directions previously specified. A specific weather condition is determined by the direction of the wind and waves along with their respective magnitudes. In this test set each weather condition has a duration of 14 minutes, of which the first seven minutes involves a change of both wind and wave magnitude from the previous weather condition. If all conditions have been run for a single direction this transition period involves a linear transition from one weather direction to the next one. The entire simulation test set spans approximately 15 hours of vessel maneuvering. The actual run time is reduced by means of running the simulation 5 times faster than the real time.

A three DOF DP controller is applied to perform station-keeping. The controller applies a single PID controller in each DOF and the output of the motion controller connects to a basic generalized inverse control allocator for distribution of the generalized force vector into individual thruster commands. Figure 9 shows how the true position compares to the position with measurement noise added (see Section III-A). The latter is the raw position output by the dGNSS system when it is operating normally. The noiseless position signal is not used for any other purpose than visualization.

1) *KF parameters:* A KF was implemented for comparison to a conventional method of DR. It requires model-dependent matrices in addition to tuning parameters. We list the applied tuning parameters along with the matrices describing the mass and damping of the simulated vessel in the following paragraphs.

$$M = \begin{bmatrix} 1.02e7 & 0 & 0 \\ 0 & 1.02e7 & 8.44e6 \\ 0 & 8.44e6 & 5.80e9 \end{bmatrix} \quad (8)$$

$$D = \begin{bmatrix} 300000 & 0 & 0 \\ 0 & 550000 & 600000 \\ 0 & 600000 & 1.38e8 \end{bmatrix} \quad (9)$$

Furthermore, the two tuneable matrices of the KF, the \mathbf{R} and \mathbf{Q} matrices had the following numerical values. Note that the values in \mathbf{R} were determined using a dataset sampled while the vessel was unaffected by environmental disturbances, while the general rules given in [6] were used for tuning the \mathbf{Q} matrix.

$$\mathbf{R} = \text{diag}([0.7, 0.7, 0.2]) \quad (10)$$

$$\mathbf{q}_1 = \text{diag}([0.1, 0.1, 0.1])$$

$$\mathbf{q}_2 = \text{diag}([1e6, 1e6, 1e6])$$

$$\mathbf{q}_3 = 0.1 \times \mathbf{R}$$

$$\mathbf{Q} = \begin{bmatrix} \mathbf{q}_1 & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{q}_2 & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & \mathbf{q}_3 \end{bmatrix} \quad (11)$$

In terms of objective, the implementation of the KF used in this paper differs from the other methods. The KF aims

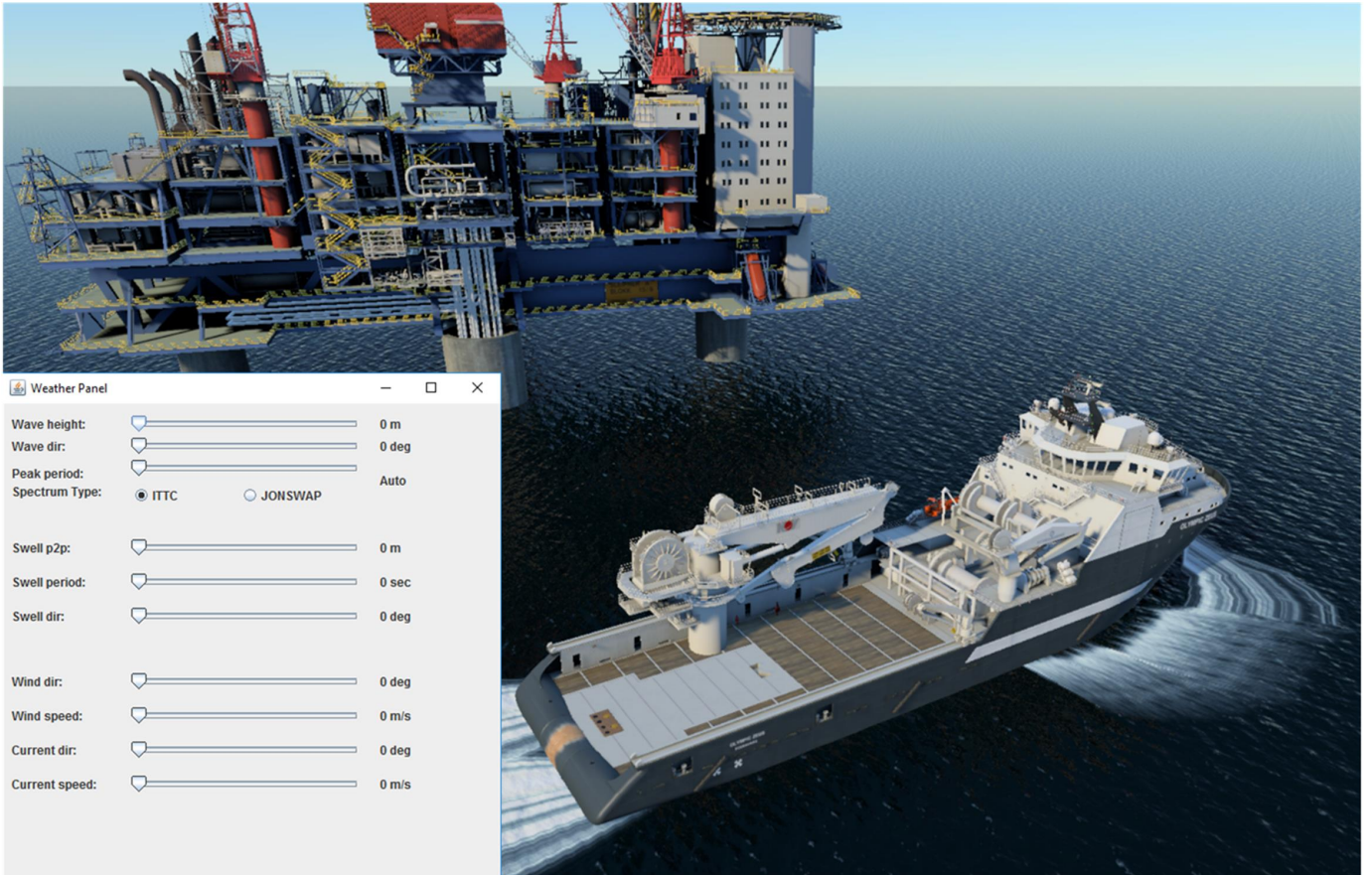


Fig. 5. A screenshot that shows the simulated environment and the panel for applying environmental disturbances.

to produce a position estimate that reflects no influence caused by zero-mean oscillatory wave forces. Thus, under normal operation we would expect to see a smooth trajectory following the mean of the measured position and heading. The other two methods aim to copy the exact behaviour of each time series, resulting in a more erratic trajectory during normal operation due to both measurement noise and wave-induced motion.

B. Case study 1: input selection

Reducing the input dimension of the network has positive effects on computation time as well as network interpretability and generalization ability. It is key to retain sections of the overall input pattern that contain useful information, which sets the stage for the method described in Section III-E: Mutual Information. MI allows for a ranking of input variable importance relative to an output variable. Therefore, input variables that offer a low relative MI value was deselected at this stage. In Table III we see the 0-1-normalized MI of the two target variables; surge velocity and sway velocity.

As shown in the "Description" column of Table III, *power* indicates the consumed power in watts of the specific thruster, *cmd* indicates the command sent to the thruster (either a blade pitch angle or an angular velocity value), and *act* indicates the feedback value measured at the thruster. Given the results in Table III and a threshold value of 0.4 we see that the

TABLE III
THE NORMALIZED AVERAGE MI VALUE OF INPUT VARIABLES RELATIVE TO THE OUTPUT VARIABLES.

Input variable	Description	Surge velocity	Sway velocity
1	Heading angle	0.0	0.08
2	Wind angle	1.00	0.69
3	Wind velocity	0.67	0.69
4	Bow thruster power	-	1.00
5	Bow thruster cmd	-	0.02
6	Bow thruster act	-	0.04
7	Stern thruster power	-	0.73
8	Stern thruster cmd	-	0.00
9	Stern thruster act	-	0.01
10	Main thruster power	0.49	-
11	Main thruster cmd	0.37	-
12	Main thruster act	0.44	-

reduced input pattern of the network predicting the surge velocity consists of input variables 2, 3, 10, and 12. For the network predicting the sway velocity the variables are 2, 3, 4, and 7. The input patterns are thereby reduced to 66 % (surge velocity) and 44 % (sway velocity) of the original input length. The dataset used for training contains 10^4 samples spaced by one second. Over the course of about 2.5 hours of simulation time, 12 randomly chosen weather conditions are run. Wave heights and wind velocities were chosen within the ranges given in Table IV.

A comparison of the performance in terms of estimated

position, relative to the sampled true position, is seen in Figure 6. It displays the mean error with/without MI over a one minute DR period for all weather conditions in the test set where the vessel was able to keep the desired position. The deselected weather conditions are highlighted in Section IV-C. As noted in Section IV-A, each individual weather condition lasts for 14 minutes, of which one minute towards the end of each weather condition was applied for the DR tests. Using the complete input vector for both the surge velocity estimator and the sway velocity estimator results in an increase in position error. Figures 7 and 8 show the result

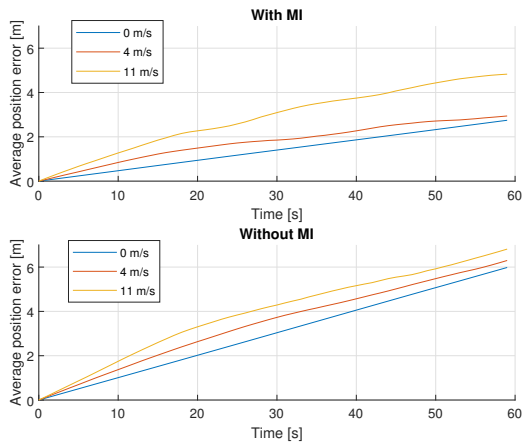


Fig. 6. The mean DR error of the LSTM method for all wind directions at wind velocities of 0, 4 and 11 m s^{-1} . Top plot: a subset of the elements in the complete input vector was extracted using MI and used as input to the LSTM model. Bottom plot: all entries in the complete input vector was used as input to the LSTM model.

of running the optimization function to determine optimized hyperparameters for the LSTM estimators. For the reduced-input estimators of surge velocity and sway velocity the following hyperparameter pairs were selected based on the lowest observed MSE value:

- Surge velocity: block number = 43, learning rate = 0.0070
- Sway velocity: block number = 26, learning rate = 0.0165

C. Case study 2: impact of the environmental variables

In this section we look at how the LSTM, SLFN, and KF perform over a wide operational range. According to the previous section, input selection is applied, resulting in the use of variables (2, 3, 10, 12) to predict the future surge velocity and variables (2, 3, 4, 7) to predict the future sway velocity (see Table III). Figure 9 shows the position of the vessel throughout the test set, with and without measurement noise. Similar to the previous section we use the position without measurement noise as reference. To evaluate the models we view the mean distance error observed during a one minute period of each weather condition. Each period of evaluation, in which DR is required, starts three minutes after the transition into the new weather condition has finished. This allows the control algorithm time to adapt to the current

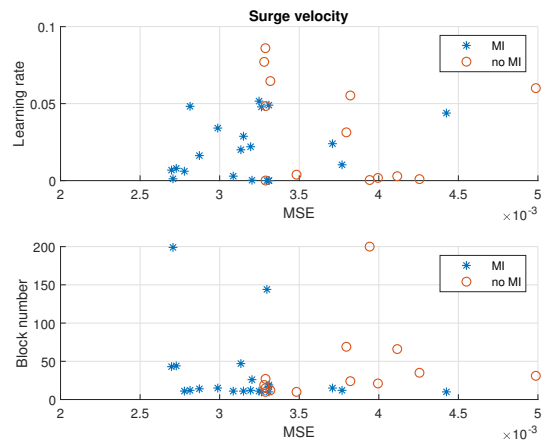


Fig. 7. Results in terms of running the LSTM hyperparameter optimization function on the two parameters learning rate and block number for the surge velocity estimation model.

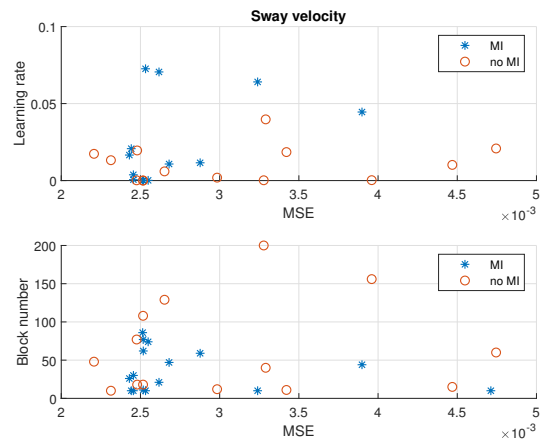


Fig. 8. Results in terms of running the LSTM hyperparameter optimization function on the two parameters learning rate and block number for the sway velocity estimation model.

environmental forces. Figure 10a shows how the distance error propagates, without any GNSS input, for the LSTM approach. The distance from the origin of the figure to each discrete weather direction is determined by Equation 12, which gives the mean position estimation error.

$$\bar{e}_{dist}[k] = \frac{1}{N} \sum_{k=1}^N \sqrt{(\hat{p}_n[k] - p_n[k])^2 + (\hat{p}_e[k] - p_e[k])^2} \quad (12)$$

TABLE IV
THE PARAMETERS OF THE SEA STATES SIMULATED AT EACH DISCRETE WEATHER DIRECTION.

Significant wave height (Hs)	Wind velocity
1 m	2 m s^{-1}
2 m	4 m s^{-1}
3 m	7 m s^{-1}
4 m	11 m s^{-1}

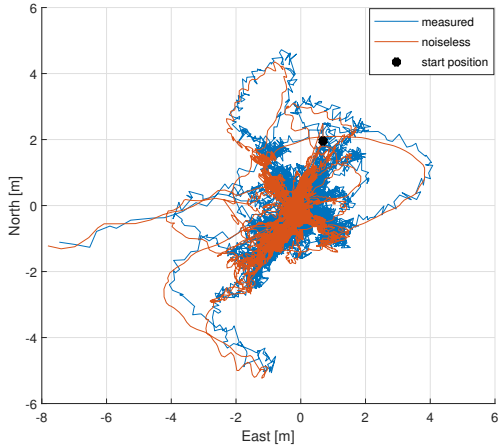


Fig. 9. Visualization of the vessel position for a part of case study 2. The noiseless position measurement (red line) is only included to provide a reference to the raw dGNSS position output (blue line).

(p_n, p_e) is the measured horizontal plane position given in the NED frame, (\hat{p}_n, \hat{p}_e) is the corresponding dead-reckoned position, and k signifies the discrete step. Figures 10b and 10c show the results of running the same test with the remaining two methods, i.e., the SLFN and the KF, respectively.

Considering the area covered by the polygons in Figure 10a, the mean error is roughly similar irrespective of weather direction and wave heights below three meters. Similar properties are seen for the SLFN method (see Figure 10b). The optimization scheme used for the LSTM method was also applied for the SLFN method. This yielded an optimized hidden neuron number of 93 for the sway velocity estimator and 55 for the surge velocity estimator. For both estimators, the optimization procedure favoured a sigmoid activation function. An increased DR error may be seen for both methods at weather directions of 270, 120, 90, and 60 degrees. At these directions and a wave height of four meters the tunnel thrusters are unable to produce sufficient thrust to withstand the environmental forces acting on the vessel. This caused saturation of thruster commands and divergence from the desired position. When a given set of thruster commands no longer cause vessel motion similar to that experienced in the training set (e.g. when the environmental forces outweigh the control forces and cause thruster saturation) the output of the estimators diverge from the true vessel velocity. The most severe effects of the saturation are seen at a direction of 120 degrees and 4 m wave height. The vessel is unable to recover the desired position in a timely fashion, causing further estimation error for all simulated conditions at the subsequent weather direction of 90 degrees.

V. DISCUSSION

The input variables related to thruster command, thruster operating point, and power do not directly give information about the motion of the vessel. However, they indirectly contain information about how the vessel moves. A thruster command, executed over a given time interval, induces forces

on the vessel, causing a change in linear/angular speed. The consumed power fluctuates both due to the thruster command and the velocity of the vessel relative to the surrounding water. Accounting for lags (see Section III-B), one may obtain knowledge of how the vessel moves by viewing thruster data. This is one of the advantages of using a data-based model: it learns such connections. To make the task of the machine learning methods easier, and make them more effective, input selection picks the most relevant input variables. Input selection also mitigates the issue of the curse of dimensionality for our problem, which is an issue for high-dimensional input patterns in regression problems [35]. The number of samples necessary to approximate a function to a certain degree of smoothness grows exponentially with the input dimension.

In this study we performed input selection on the basis of the mean MI (see Section III-E) for an input variable containing lags according to, for example, variable x_1 of Equation 7. This allows for an uninterrupted representation of the selected variable. Another strategy would be to select the entries of the total input pattern (see Section III-E1) that has an MI value greater than some threshold, which does not leave the inter-variable spacing intact, but ensures that all entries in the selected pattern have a given MI content relative to the target variable.

The results produced in Section IV-B show the increased performance gained by selecting input variables that provide a certain amount of information about the output variable, omitting the remainder of the original input variables. Viewing the optimization results in Figures 7 and 8, we see that only the surge velocity estimator benefits from applying MI, at least in terms of the MSE derived from a validation set consisting of 10 % of the samples in the training dataset. This amounts to roughly 1000 samples. Although the sway velocity estimator displays a slight decrease in performance when applying the reduced input pattern, the overall effect of MI is positive. As the input selection process of the two estimators are separate, one may choose to implement one, or both, of the reduced input patterns in order to maximize the expected DR performance. Figure 6 displays how the estimated position, using input vectors selected by MI, diverges more slowly compared to applying the original input pattern during a GNSS dropout. As MI was shown to aid the LSTM model (see Section III-D) in terms of reducing the position estimation error, it was applied to both machine learning models for the second case study, shown in Figure IV-C. Of the two, the LSTM performed best with a mean distance error of less than 2 m for wave heights below 3 m. The measurements of thruster-related states (power consumption, setpoint, and feedback) were assumed to be noise-free.

The KF, described in Section IV-A1, has similar performance relative to the LSTM for wave heights of 1 m. When wave heights of 2, 3, and 4 m affect the vessel, the LSTM provides consistent DR position estimates while the KF error increases. The KF error increase is, in part, due to the linear relationship between a thruster command and the resulting force output of a thruster assumed in a regular KF. Due to the lack of measurements to facilitate a corrector-function, the DR position is driven solely by the vessel model and the

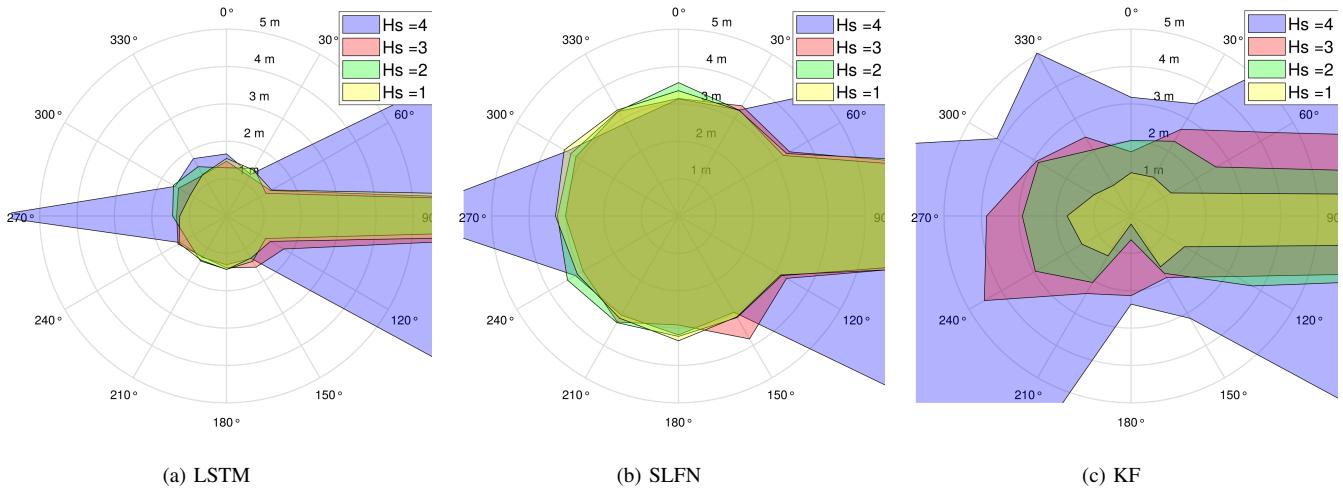


Fig. 10. Results of mean position estimation error given in the horizontal plane for the LSTM, SLFN and KF model for case study 2. Each data point shows the mean position estimation error during a one-minute DR period. Hs denotes the significant wave height in meters.

thruster command input vector. Similar to the LSTM model the SLFN model displays consistent DR position estimates, although at a larger magnitude. When wave heights exceed 3 m, the SLFN outperforms the KF. As the implemented KF requires a significant number of parameters to be set, an optimization scheme to derive optimized KF parameters might offer a more balanced comparison between the three methods.

While the KF requires no initialization process, it does require a mathematical model of the vessel. Machine learning models create an equivalent model based on data. That is why, from a cold start, the machine learning algorithms require a certain amount of time to construct and train the estimator. During this time the DR functionality is unavailable. While this is inconvenient, it may be remedied by performing the initialization process at regular intervals, or continuously, in order to have a DR model that is current with respect to the state of the vessel. Thereby, it can seamlessly provide position estimates to a vessel operator, or the underlying automatic control system of a vessel, during a position reference system outage. This requires either maintaining a window of the most recent samples to perform batch training or feeding each individual sample to an online training algorithm for each of the two machine learning methods. This is particularly important as we make the assumption of constant mean environmental forces during the DR process. If an “old” model is used, it may not reflect the characteristics of the current environmental state. In our approach the training set consisted of 12 random weather conditions, which was assumed to be representative of the complete set of possible weather conditions. The authors acknowledge that the relative performance of the methods proposed in this study is highly affected by the value of the parameters of each method.

VI. CONCLUSION

Through the simulation studies we have compared the proposed LSTM NN method with a conventional KF and a

SLFN model. When no position or velocity measurements are available, the three methods utilize their own established model together with their related model inputs. For the KF these are given by the vessel model as thruster commands and forces due to wind. But for the machine learning methods, an initial input pattern was selected, then input selection reduced this to a vector comprised of about two-thirds of the most relevant entries of the original input vector. This offered an improvement in terms of position estimation performance.

Findings suggest that the models created by machine learning methods offer comparable performance in terms of position error drift, without requiring any vessel-dependent parameters. This shows that the dynamics of the vessel may be modelled without the development and tuning of a mathematical model. However, machine learning methods offer no guarantees of convergence, being inherently black-box. Therefore future research should provide a deeper investigation into how to establish a measure of confidence into the behaviour of the machine learning methods.

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