Application of Reinforcement Learning Technique for Parameter Identification of Coupled Heave-Pitch Motion Equations Using Measured Response at Sea

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ABSTRACT

This study introduces a technique for identifying the parameters in the equation describing the heave/pitch motion of a ship by using only its measured response at sea. The parameters being identified are the direct and cross coupling damping and restoring parameters. These values are identified using a reinforcement learning technique. The proposed method would be suitable in identifying the direct and cross coupling damping and restoring parameters for a ship heaving and pitching under the action of unknown excitations effected by a realistic sea state. Published data, results of a commercial seakeeping package and recorded data for a ship's heave and pitch motions in random seas are used to test the accuracy and the validity of the method. It was shown that the method is reliable in the identification of the parameters of the coupled equation of the heave-pitch motions using only the measured response at sea.

KEY WORDS: system identification; heave; pitch; reinforcement learning; equation of motion

INTRODUCTION

Predicting ship response to incident waves has been investigated since the 1960s (Salvensen, et al., 1970). Heave and pitch motions are the most studied among the six degrees of freedom of a ship in a seaway. The level of accuracy of predicted heave and pitch motions is higher than other degrees of freedom. Strip theory is the most popular method for analytical predictions of heave and pitch motions; however, strip theory often delivers inaccurate results in extreme sea states.

Several other methods have been developed to predict vessel response to incident waves. Computational Fluid Dynamics or seakeeping computer codes based on potential flow theory (WAMIT, 2018) (ShipX, 2018) (Motions, 2018) play an increasingly important role in investigating and predicting the hydrodynamic performance of ships and offshore structures. However, the linearization of the problem in most potential flow codes neglects several important effects. Firstly, pressure integration is performed over the time-average wetted surface, neglecting changes of the wetted surface due to waves and ship motions. Secondly, the influence of the changing wetted surface on the flow and hydrodynamic forces is not considered. While CFD simulations do not require the same simplifications, the computational cost is too great for many use cases. Recently, work on modelling the non-linear aspects of seakeeping using time-domain methods has become more common (He & Kashiwagi, 2014a) (Jiang, et al., 2015).

For a considerable time, model tests have been (and arguably still are) the most reliable method for determining ship reactions in waves. However, the effect of scaling should not be ignored. There is a growing tendency to include uncertainty evaluations when presenting experimental results of seakeeping tests as recommended by the International Towing Tank Council (ITTC), although this is a difficult task.

Accurately Identifying the hydrodynamic parameters in the equations describing the coupled heave-pitch motions of a vessel in a realistic sea state provides a method for accurately estimating the ship's response. System identification (SI) is a methodology for building mathematical models that provide relationships between the input and output variables of dynamic systems. This approach avoids the errors due to scale effects, simplifications and approximations that affect other approaches (e.g. the two-dimensional method of calculation used in strip theory). However, access to real measured responses is required.

The parametric identification of the equations of motion of a ship has been dealt with by several authors. Abkowitz and Liu (1988) used a Kalman Filter approach to identify the hydrodynamic coefficients in the maneuvering equations of a ship. Roberts et al. (1994) initiated an approach that is based on the use of a combination of Markov process theory and statistical linearization techniques. Another fit technique known as Neural Network Identification has been developed, which is loosely based on the human brain, and does not use a physical model. Bhattacharyya and Haddara (2006) used artificial neural networks (ANN) and spectral analysis methods to identify the hydrodynamic derivatives in the mathematical model involving ship and marine vehicle motions. Selvam and Bhattacharyya (2010) attempted to use a system identification approach, specifically the reverse multiple input–single output (R-MISO) method, for coupled heave–pitch response of a ship moving with uniform forward speed in random ocean waves. Dai et al. (2014) used an opposition-based particle swarm optimization algorithm to identify coupled heave and pitch motions.

Haddara and Xu (1999) modelled the coupled heave-pitch motion of a ship in random seas as a multi-dimensional Markov process. They used Fokker-Planck equation to derive the random decrement equations for the coupled heave–pitch motion. The parameters in these equations were then identified using a neural network approach. They validated the model using numerical simulations and experimental results. Previously, authors used reinforcement learning techniques to identify the damping and restoring parameters of roll equation of motion for a ship in random seas (Javanmardi, et al., 2019).

Reinforcement learning techniques where used in this study to attempt to identify the unknown parameters of equation of motions of the coupled heave-pitch of a ship in random seas.

HEAVE AND PITCH EQUATIONS OF MOTION

The coupled heave–pitch motion of a ship in a realistic sea can be described by two linear second order ordinary coupled differential equations in the following form (Haddara & Xu, 1999):

$$(m+a_{33})\ddot{x}_3 + b_{33}\dot{x}_3 + c_{33}x_3 + b_{35}\dot{x}_5 + c_{35}x_5 = f_3(t) \quad (1)$$
$$(I_{55}+a_{55})\ddot{x}_5 + b_{55}\dot{x}_5 + c_{55}x_5 + b_{53}\dot{x}_3 + c_{53}x_3 = f_5(t)$$

Where m is the mass of the ship, and I_{55} is the mass moment of inertia of the ship about a horizontal axis passing through the centre of gravity of the ship. a_{ii}, b_{ij}, c_{ij} (i,j = 3, 5), are the added mass and added moment of inertia, and the damping and the restoring coefficients in heave and pitch, respectively. $f_3(t)$ and $f_5(t)$ are the exciting force and moment for heave and pitch, respectively.

Eq. 1 can be rewritten as:

$$\ddot{x}_3 + B_{33}\dot{x}_3 + C_{33}x_3 + B_{35}\dot{x}_5 + C_{35}x_5 = F_3(t) \quad (2)$$
$$\ddot{x}_5 + B_{55}\dot{x}_5 + C_{55}x_5 + B_{53}\dot{x}_3 + C_{53}x_3 = F_5(t)$$

The exciting force/moment per unit virtual mass/moment of inertia of the ship is given in the following form:

$$F(t) = f\sin(\omega_e t + \emptyset) + \acute{f} \quad (3)$$

Where ω_e is the incident frequency of the exciting force/moment, $\emptyset$ is phase angle and $\acute{f}$ is a constant force/moment due to some mean bias (wind, loading, etc).

By substituting Eq. 3 into Eq. 2:

$$\begin{aligned}\ddot{x}_3 + B_{33}\dot{x}_3 + C_{33}x_3 + B_{35}\dot{x}_5 + C_{35}x_5 &\\ = f_3\sin(\omega_{e3}t + \emptyset_3) + \acute{f}_3 &\\ \ddot{x}_5 + B_{55}\dot{x}_5 + C_{55}x_5 + B_{53}\dot{x}_3 + C_{53}x_3 &\\ = f_5\sin(\omega_{e5}t + \emptyset_5) + \acute{f}_5 &\end{aligned} \quad (4)$$

To solve Eq. 4, all coefficients and exciting force/moment parameters should be known, which is undoubtedly a difficult task. The main objective of this study is to determine if system identification techniques using reinforcement learning are a reliable and robust method of identifying the parameters involved in the equation describing the coupled heave-pitch motion of a ship in random seas using only its measured random response.

REINFORCEMENT LEARNING TECHNIQUES

Machine learning techniques can be divided into 3 broad categories—supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is used when a property (*label*) is available for a certain dataset (*training set*) but is missing and needs to be predicted for other cases. Unsupervised learning is used to discover implicit relationships in a given *unlabelled* dataset. Reinforcement learning technique falls between these two extremes—there is some form of feedback available for each predictive step or action, but no precise label. Using supervised learning techniques such as ANN to find the parameters in the equation of heave/pitch motion may not be the best approach. To train an ANN, a set of labelled output is required. In addition, to use back propagation techniques, it is usually necessary to calculate the error gradients of outputs and propagate them backward through the network and correct the weights and biases. The only available data to evaluate the network is the difference between the predicted heave/pitch and the measured heave/pitch; however, the number of the ANN output in this case equals the number of unknown parameters in the equations of motion (Eq. 4). Therefore, finding the error of each output or allocating each ANN output to share the error is not straightforward.

Since the only available data to evaluate the coefficients are heave and pitch errors, the difference between the measured heave/pitch magnitude and the predicted, and there is not any set of labelled output for the parameters in the equation, it was decided that reinforcement learning techniques are more suitable than supervised methods.

Reinforcement learning techniques compute the utility of the actions without a model for the environment. It uses the expected reward from the current action to help find the optimal action. During this process the agent learns to move around the environment and understand the current state. The optimal policy is taking the action with the highest reward. In this case, the state is the required coefficients and reward is the inverse absolute error. This means that the goal is the state for which the error is equal to zero (reward is infinity at this point).

To Identify the coefficients using reinforcement learning, all coefficients (B_{ij}, $C_{ij}, f, \omega_e, \emptyset, \acute{f}$) are initialized randomly (current state). According to the heave/pitch equation (Eq. 4), these coefficients are damping coefficients (B_{ij}), restoring coefficients (C_{ij}) and parameters related to the excitation ($f, \omega_e, \emptyset, \acute{f}$).

The error (E), which is the difference between the measured heave/pitch data and the predicted heave/pitch can be calculated for the current state. To find the next state, a step (ΔC) is considered. The possible coefficients could be $C_{inew} = C_i \pm \Delta C_i \;\; i = 1,2,\dots,n$.

Therefore, the next possible states could be any combinations of C_{inew}. The error caused by all possible combinations will be calculated. Since the optimal policy is taking the action with the highest reward, the combination that generates the minimum error (maximum reward) will be selected as the next state. Then those coefficients are chosen as the current coefficients which means this state is considered as the current state. This process continues until reaching an acceptable error value (the goal state). Finally, the coefficients that generate an acceptably low error are selected as the result of system identification.

There are some parameters which have effect on the convergence and the cost (CPU time). General speaking, having a rough idea about the coefficients makes the search domain smaller and choosing correct size of step (ΔC) can decrease the simulation time.

In this technique, direct and cross coupling hydrostatic terms, direct and cross coupling damping terms, and hydrodynamic force (moment) acting on ship will be identified using only the heave and pitch responses in random seas.

VERIFICATION OF THE PROPOSED ALGORITHM

To verify this algorithm, a MATLAB program was developed based on the algorithm above to find the unknown parameters of Eq. 4. The displacement, speed and acceleration of heave and pitch are considered as the input of the program. The program then finds coefficients that satisfy Eq. 4. This program has been compared to results from Haddara and Xu (1999), to data generated using the seakeeping code SEAWAY and real measured data. Real data was recorded aboard a bulk carrier in random seas using an “iHeave”; an inertial motion device developed by

OMC International to accurately measure heave, roll and pitch motions (Hibbert & Lesser, 2013).

Numerical simulations of free decay of coupled heave and pitch motions presented in (Haddara & Xu, 1999) were used to verify the proposed algorithm. Numerical simulations were obtained by integrating Eq. 4 which describes the coupled heave–pitch motion of a ship. The vessel's coefficients corresponding to those motions are presented in Table 1. The MATLAB program then was used to predict the damping and restoring coefficients.

Table 1: Virtual Vessel's coefficients (Haddara & Xu, 1999)

B_{33}	2.824	B_{55}	2.632
B_{35}	0.158	B_{53}	0.58
C_{33}	34.092	C_{55}	30.78
C_{35}	0.238	C_{53}	0.629

Figs. 1~2 show comparisons of the heave and pitch predicted by SI to free decay heave and pitch responses generated by the numerical integration as presented in (Haddara & Xu, 1999). The parametric identification of the random decrement equations using the neural network approach presented in (Haddara & Xu, 1999) are shown in Figure 3 and Figure 4. By comparing the two approaches, it was concluded that the reinforcement method introduced in this study (Figs. 1~2) is significantly more accurate than the method used by Haddara and Xu (Haddara & Xu, 1999) (Figs. 3~4).

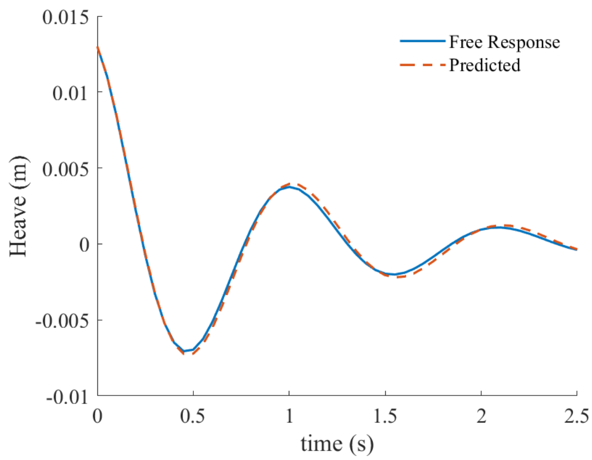


Figure 1: Comparison of benchmark data and calculated heave motion by SI

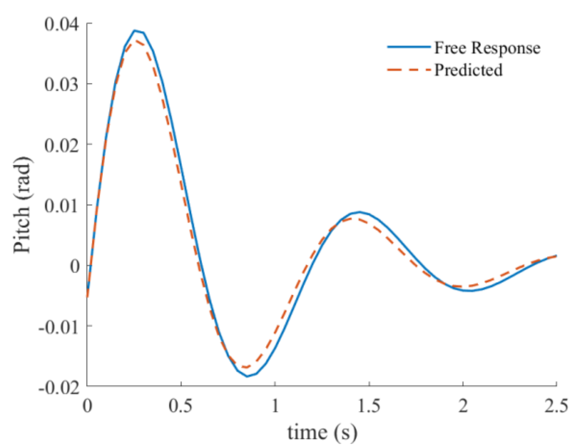


Figure 2: Comparison of benchmark data and calculated pitch motion by SI

A container vessel (S-175) was modelled using the commercial seakeeping package SEAWAY. Calculations were made for a range of incident frequencies and angles at a constant vessel forwards speed of 7 knots.

The coefficients and excitations predicted by SEAWAY were used to generate the vessel's heave and pitch responses as benchmarks to test the system identification program. The responses were used as inputs to the system identification program to predict the corresponding coefficients. In total, 34 different coefficients were considered from the results of the container ship simulation in different wave conditions with SEAWAY.

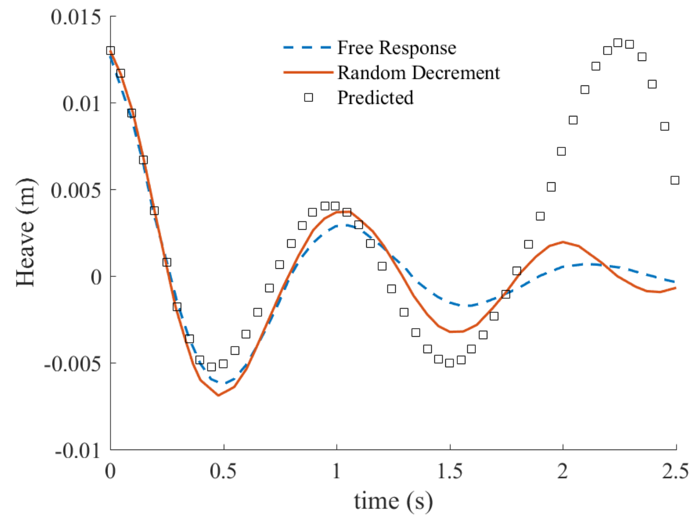


Figure 3: Prediction results for heave random decrement obtained from simulation data (Haddara & Xu, 1999)

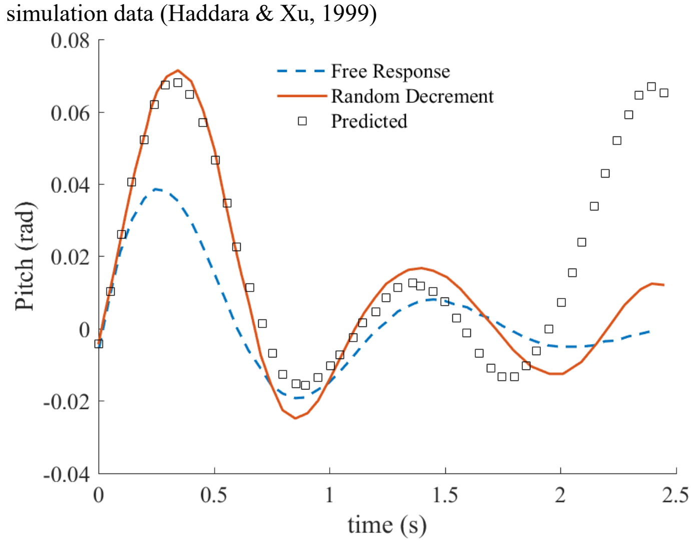


Figure 4: Prediction results for pitch random decrement obtained from simulation data (Haddara & Xu, 1999)

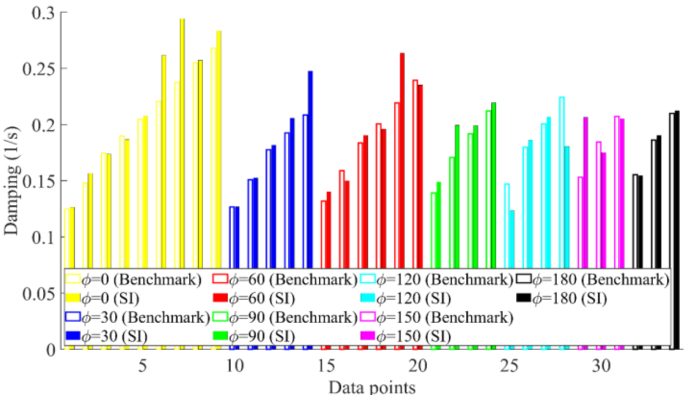


Figure 5: Comparison of direct damping coefficient (B_{33}) at different wave incident angles

Figure 5~9 compare the direct and cross coupling coefficients and the excitation force amplitudes of heave motions predicted by the system identification method (SI) and benchmark values (SEAWAY simulation results) at different incident angles. It should be mentioned that the accuracy of pitch motion results is very similar to this.

It is concluded that the system identification method proposed in this study can accurately predict the coefficients of the heave/pitch equation of motion. Inaccurate predicted coefficients can easily be distinguished by comparing the predicted motion to the measured data. It should be mentioned that these are the results of a first attempt at applying these techniques and there is high chance of improving the accuracy of coefficients by changing the initial step size and values or modifying the search algorithm.

In the next step of validation, a series of data recorded by iHeave for a full-scale bulk carrier in real seas was utilized. Some of the vessel parameters are outlined in Table 2. Due to the random nature of real seas, environmental conditions and wave parameters could vary for each oscillation in the motion time series. Therefore, it is expected that values for the coefficients related to the heave and pitch excitations will not be constant for whole time series, but it can be assumed those parameters remain constant during a single oscillation.

To account for this, at the pre-processing stage, the recorded data was split into single oscillations before being used as the input to the program. A script was written to automate this. This script splits the heave data to single oscillations and splits the pitch data at the same points as the heave. Since the heave frequency is not necessarily equal to pitch frequency, for each heave oscillation the corresponding pitch can be more or less than a complete oscillation which schematically is illustrated in Figure 10.

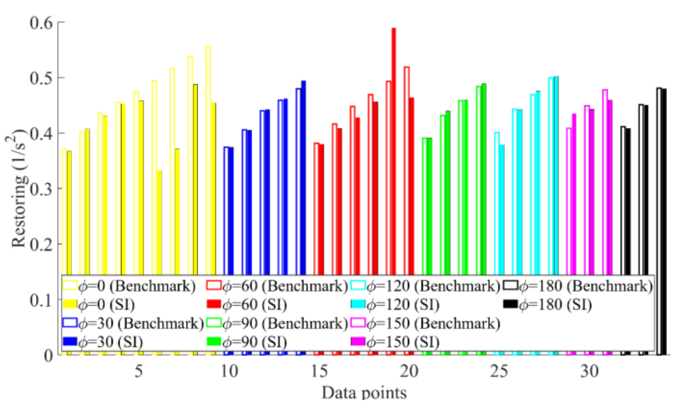


Figure 6: Comparison of direct restoring coefficient (C_{33}) at different wave incident angles

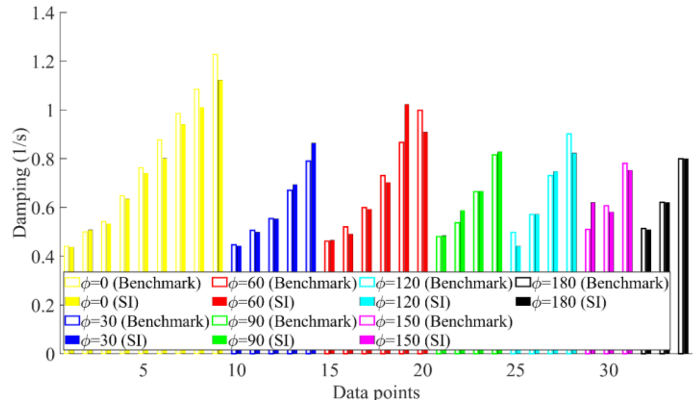


Figure 7: Comparison of cross coupling damping coefficient (B_{35}) at different wave incident angles

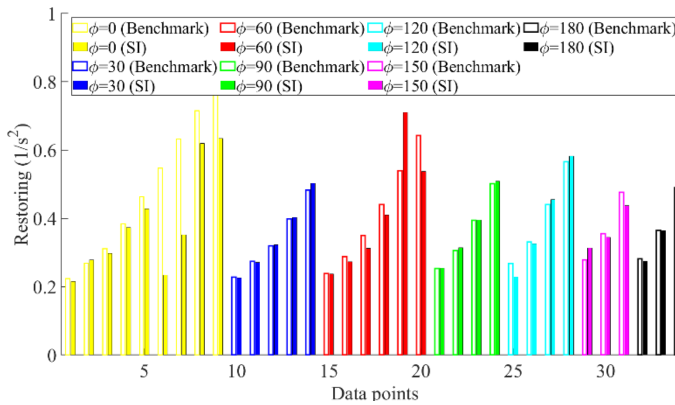


Figure 8: Comparison of cross coupling restoring coefficient (C_{35}) at different wave incident angles

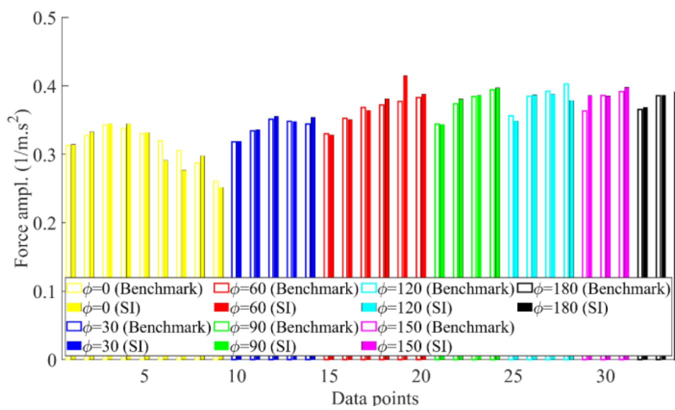


Figure 9: Comparison of excitation force amplitudes (***f***) at different wave incident angles

The pre-processed data was then used in the SI script to find the coefficients of motion for the vessel. Figure 11 shows comparisons of some measured heave oscillations in realistic sea waves with that predicted by SI. The magnitudes of predicted heave are acceptably close to the measured values. The differences seen in the heave speed and heave acceleration plots could be caused by errors in the numerical differentiation that was used to calculate the speed and acceleration of from the measured heave magnitude.

Table 2: Full scale vessel's particular

Vessel Class	Bulk Carrier	KG (m)	15
LBP (m)	278	Draught (m)	9.95
Beam (m)	45	GM_f (m)	9.64

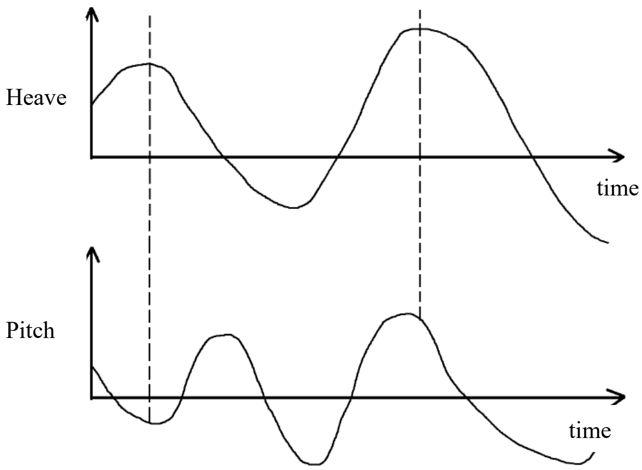
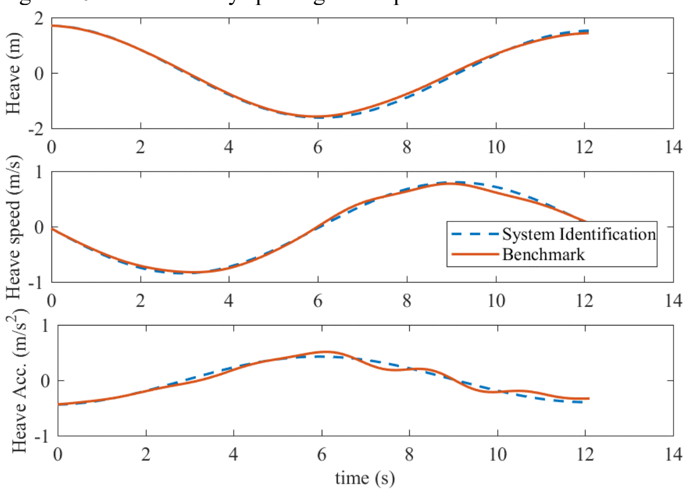
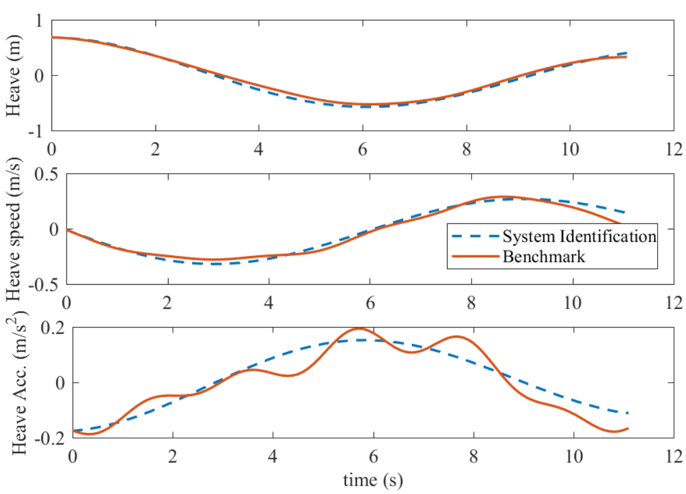
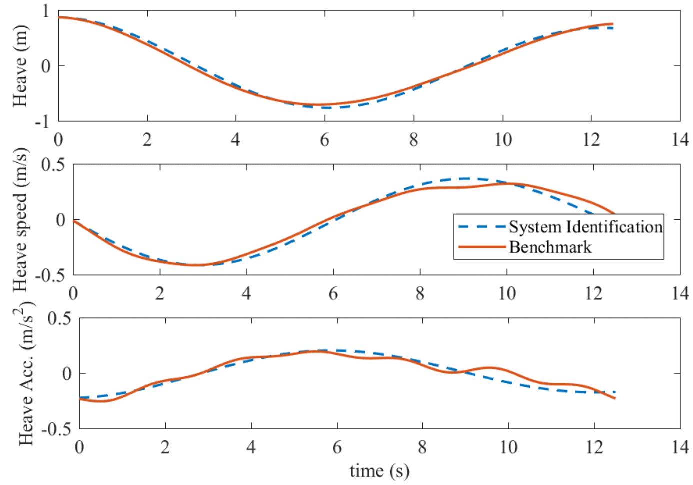


Figure 10: Schematically splitting heave/pitch data







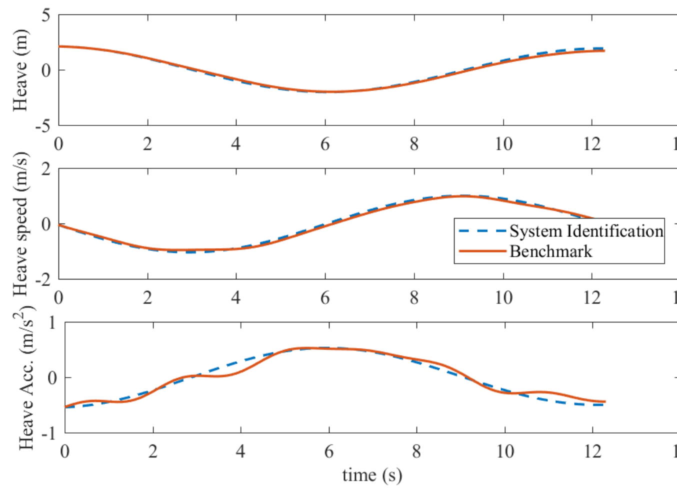


Figure 11: Comparison of some measured heave data in realistic sea waves with predicted heave by SI

CONCLUSION

In this study a novel method has been developed for identifying the direct and cross-coupling coefficients in the equations describing the heave/pitch motions of a ship by using reinforcement learning techniques.

By having access to measured heave and pitch data and using the proposed system identification method, direct and cross coupling restoring, and damping coefficients of the vessel can be found. Since this technique does not involve any simplifications or assumptions, it is expected that this method can accurately estimate the coefficients when accurate measured motion data is available. A series of data from literature, results of a commercial seakeeping package and real measured data for a bulk carrier in random seas are used to verify the proposed method.

It was concluded that the method is accurately able to identify the parameters of the coupled equation of the heave-pitch motions using only the measured response at sea.

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