Scientific Journals
of the Maritime University of Szczecin

Zeszyty Naukowe
Akademii Morskiej w Szczecinie

2022, 72 (144), 65–74
ISSN 1733-8670 (Printed)
ISSN 2392-0378 (Online)
DOI: 10.17402/535

Received: *16.03.2022*
Accepted: *22.09.2022*
Published: *31.12.2022*

Ship nonlinear roll motion identification using artificial neural network

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Keywords: nonlinear roll motion, dynamic identification, DTMB 5415, roll decay, artificial neural network

JEL Classification: C18, C45, C61, C63

Abstract

The solution of the nonlinear equation for a ship's rotational motion around its longitudinal axis, even with simplifying assumptions, is complicated. This oscillatory motion, which is known as the roll motion, is generated when the ship sails in the waves, and the irregular behavior of the waves causes time-varying dynamics. Calculating the ship's roll response is possible by determining roll equation coefficients. In the current study, the coefficients were determined from the dynamic response of the ship using a training feed-forward neural network. The training was carried out in two modes: as a free swing in calm water and forced oscillation in irregular waves. The DTMB 5415 vessel was selected as the case study ship. The results of the simulation by the neural network were validated by numerical analysis and model test results.

Symbols and abbreviations

Symbol	Description, unit
A	Total inertia coefficient, kg·m^2
B	Damping coefficient, kg·m^2/s or ship breadth, m
C	Restoring coefficient, N·m
dr	Roll decrement, deg
Δ	Ship displacement, kg
F	Environmental force, N·m
GZ	Ship righting arm, m
K_{xx}	Mass radius of gyration around x-axis, m
K'_{xx}	Added mass radius of gyration around x-axis, m
K''_{xx}	Total mass radius of gyration around x-axis, m
LCB	Ship longitudinal center of buoyancy, m
VCG	Ship vertical center of gravity, m
I_{xx}	Inertia coefficient, kg·m^2
t	Time, s
t_S	Swing period, s
AP	Ship aft perpendicular
d_P	Network desired output
Fn	Froude number
f	Neural network transfer function
FP	Forward perpendicular
mu	Network training error
NN	Neural Network

w, u, s, v	Weight coefficient in NN layers
x	NN inputs
y	NN layers outputs
Y	NN transfer function outputs
z_P	Network normal output
WL	Water line
μ, η, δ	Training error back propagation coefficient
α	Training momentum coefficient

Introduction

Rotational motion about the longitudinal axis, referred to as roll, is usually created when a ship moves through the waves. This motion is important in the seakeeping performance of the vessels. Many dynamic effects such as seasickness, equipment performance, and personnel performance, depend on this motion. The simulation of the roll motion of the ship is necessary in the design phase for determining the seakeeping performance of the vessel. A simple and practical method for the calculation of seakeeping is the strip theory or potential method, which is elaborated in the primary references of seakeeping. The investigation of relevant articles and references shows that this method provides acceptable results for the ship's vertical plane motions, including the pitch and heave. However, for the roll motion of the ship, especially in nonlinear conditions, this method gives significant errors due to its failure to consider damping effects due to fluid viscosity. Calculating the roll response is possible through the definition of the nonlinear hydrodynamic coefficients of the roll motion equation.

There are numerous articles and publications related to roll motion and ship motion control. The reference books, "Dynamics of marine vehicles" written by R. Bhattacharyya, 1978, and "Principles of Naval Architecture" by Edward V. Lewis, 1989, are the primary references for such articles. The dynamics of roll motion in this paper have been retrieved from these references.

Mahfouz (Mahfouz, 2004) dealt with the determination of the nonlinear equation of roll motion by measuring a ship's response in the sea. In this study, the linear and nonlinear coefficients and parameters were calculated by using an NN for the free oscillation and the roll motion oscillation under a regular exciting moment. The ship's roll motion response was considered as the input and the exciting roll moment as the output of the network. Xing and McCue (Xing & McCue, 2010), in a similar manner to Mahfouz (Mahfouz, 2004), used a feed-forward NN. In this network, the roll motion responses are input values and the roll motion equation coefficients and the exciting moment are the output values from which, after being placed in the roll motion differential equation, the roll motion response is extracted again and compared to the network's input. This error is used for the adjustment of the network's weights. The problem of this method is in the training of the NN. Generally, in NN-supervised training, the difference between the desired output and network output comprises the error function, which is used for backpropagation and weight modification. In this study, the network outputs are coefficients and exciting forces, and there are no desired values for these parameters, so the network outputs used for solving the motion equation, the response extracted, and the difference between the extracted response and the input response form the error function. Due to the complexity of the relationship between the response error and network output, the network has uncertainty. This uncertainty in the irregular motion leads to erroneous results, and its application in controlling the motion leads to the intensification of motion due to inadaptability (Perez & Blanke, 2002).

In many of the articles, such as those of Alarçïn (Alarçïn, 2007), Ghassemi et al. (Ghassemi et al., 2010), Oskin et al. (Oskin, Dyda, & Markin, 2013), and Awad et al. (Awad, Elgohary, & Mohamed, 2018), the NN was paralleled by linear control systems, such as PID or LQR. The network was trained to imitate controller behavior, and its performance was compared to control systems. In these studies, artificial NNs were more stable and performed better.

Hou et al. (Hou, Zou & Liu, 2018), in a similar study to that of Mahfouz (Mahfouz, 2004), determined the nonlinear damping and restoring moments by a combination of the random decrement technique (RDT) and support vector regression. In the study by Hou et al., damping and restoring moments were considered as a combination of linear and nonlinear parts. Auto and cross-correlation functions and training samples were used to find the linear part, while by using the training sample and random decrement signature, nonlinear parts were identified, and by the numerical solution the roll motion was simulated. In the study by Hou et al., a semi-regular exciting force was assumed.

Method of work

Dynamic identification of floating structures is an essential field in marine studies. The design of a ship's dynamic control systems is viable when the dynamics of the ship as a system are identified. The determination of the nonlinear hydrodynamic coefficients of roll motion is not possible by simplifying assumptions and is very complicated in irregular waves. Recording the dynamic response using laboratory tests or during sailing is possible. However, the roll exciting moment cannot be recorded, which is one of the problems in the definition of the coefficients. Dynamic system identification in seakeeping is complicated and requires time and costly experiments.

In the current study, a method for simulation of the nonlinear roll of the ship is proposed, employing a feed-forward artificial NN. The input layer of this network included the motion response, and the output layer of this network was the roll motion equation coefficients. This network had three hidden layers with 27 neurons with bipolar sigmoid functions and linear output. The desired values for the output included the coefficient of the rotational moment of inertia, damping, and the restoring coefficient.

The training of the NN was carried out in two phases. In the first phase, the network was trained using free rolling in calm water and various speeds, and the simulation results were compared to the test results. In the second phase, this network was trained by CFD simulation in irregular waves. Finally, the simulation from the NN was compared with the CFD simulation. The investigations of the current study indicated that the two-phase training was very effective, and that training convergence in the second phase was viable by using the first stage training as the initial conditions.

Table 1. The specifications of the prototype ship

Particular	Prototype
Length overall, m	153.230
Length between perpendiculars, m	142.000
Breadth max molded, m	20.546
Breadth molded on WL, m	19.060
Draught molded on FP, m	6.150
Draught molded on AP, m	6.150
Displacement, m^3	8431.800
Wetted surface area, m^2	2972.600
LCB Position aft of FP, m	71.970
Transverse metacentric height, m	1.950
VCG, m	7.510
Natural period of roll, m	11.500
Block coefficient	0.507
Mass radius of gyration around *x*-axis	7.620
Mass radius of gyration around *y*-axis	35.500
Mass radius of gyration around *z*-axis	35.500
Max Speed, m/s	15.432

The DTMB 5415 ship was used as the case study model. This model is a well-known ship research model that is used by researchers, and the results of the studies are shared on the model's reference website. The dimensions of the selected model are the laboratory model IHRR with a scale of 46.588. It has a length of 3 meters and a weight of 83.4 kg. Table 1 presents the case study model specifications (Irvine, Longo & Stern 2004).

Governing equations

The roll motion, in common with many dynamic phenomena, follows Newton's Second Law. The nonlinear change of the equation coefficients leads to the impossibility of a direct solution. However, it can be solved using numerical methods. The equation for this motion can be written as follows:

$$A\ddot{x} + B\dot{x} + Cx = F \tag{1}$$

In this equation, (A) is the rotational inertia coefficient, (B) is the damping coefficient, and (C) is the restoring moment coefficient. The coefficients are dependent on the ship's dynamics and environmental conditions. Based on this equation, the exciting moment from sea waves applied to the ship causes the roll acceleration of the object (first term), a part of it being lost as damping (second term), and a part of it is used for increasing the object's potential in the form of restoring moment (third term). As a simple description, the ship roll motion is similar to the vibrational motion of its mass acting as a simple-mode spring moving in a free or forced manner. An oscillating motion of the ship is usually created due to its movement through the waves. Regarding the irregularity of the waves, the exciting moment would also be irregular. On the other hand, the shape of the ship's hull, equilibrium, and wave heading lead to the variability of the restoring coefficient. The inertia coefficient and damping coefficient of the ship are also a function of the rolling angle and the forward speed.

Artificial neural network

An artificial NN is a simplified model of the brain's NN. Figure 1 shows the simplified mathematical model of an artificial neural cell. In this model, an input value (x), after being strengthened (or weakened) by the parameter (w), with the size of (xw), enters the neuron in the form of an electrical signal. The summation of input signals obtained as $[(\Sigma xw) + v]$ undergoes another operation or process, which is technically called a "transfer function". The input of this box is $[(\Sigma xw) + v]$, and the output is designated as y. Parameter w is called the "weight parameter" (Jain, Mao, & Mohiuddin, 1996).

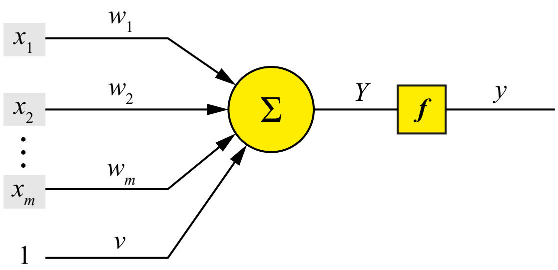

Figure 1. Neuron's mathematical model

An NN typically consists of many cells. The behavior of the network, in addition to being dependent on the transfer functions, depends on the weight parameters. In such a network, the weight parameters must be initialized and adjusted, so that the network has an appropriate mapping between input and output values. This process, in NN science, is called the training process. In practice, the transfer functions are usually a type of sinusoidal function, hyperbolic tangent, sigmoid, or the like. This transfer function transforms the input signals' combination to an output signal whose value can be between −1 ~ 1 or 0 ~ 1 (Jain, Mao & Mohiuddin 1996). Two or more neurons can combine in a layer of the network. Also, a network may have one or several layers. Figure 2 shows a multilayer network.

Network training is based on the network error, which is the difference between the network output and the desired output. One of the well-known and practical methods of network training is backpropagation or, in other words, adjustment of the weights of the layers based on the output error function. In the next section, this method is presented for the roll motion artificial NN.

Nonlinear roll artificial neural network structure

Figure 3 shows the structure of the NN used in the current study. The input matrix was the ship's motion response, including the Froude number, displacement, velocity, and acceleration of the roll, pitch, and heave motions. Considering the values of the pitch and heave motions means that the effects of other degrees of freedom on the roll motion coefficients are considered, and this is a prominent feature of this study.

The input layer of this network was the following matrix.

$$\text{Input} = \left[\text{Fn} \;\; \Delta \;\; x_1 \;\; \dot{x}_1 \;\; \ddot{x}_1 \;\; x_2 \;\; \dot{x}_2 \;\; \ddot{x}_2 \;\; x_3 \;\; \dot{x}_3 \;\; \ddot{x}_3\right]^{\mathrm{T}} \quad (2)$$

Indices 1, 2, and 3 were indicative of the degrees of freedom of the roll, pitch, and heave, respectively in equation (2). The output matrix had three arrays, shown as the following matrix (Eq. (3)).

$$\text{Output} = \left[A \;\; B \;\; C\right]^{\mathrm{T}} \quad (3)$$

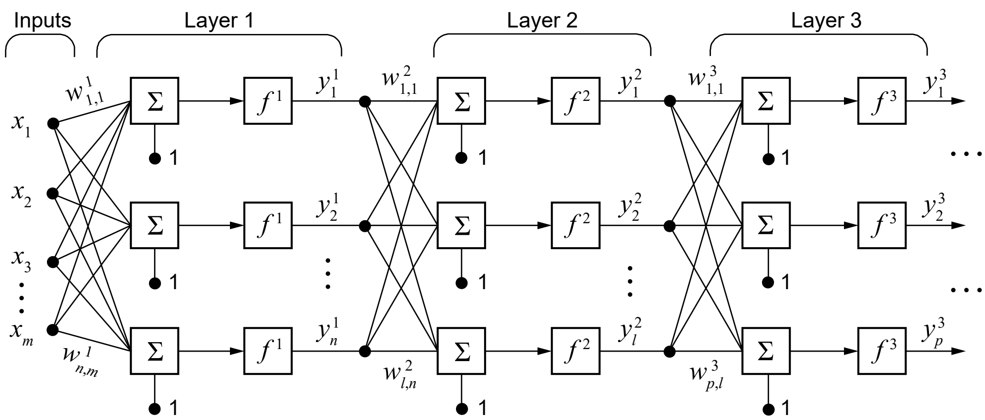

Figure 2. Multilayer network

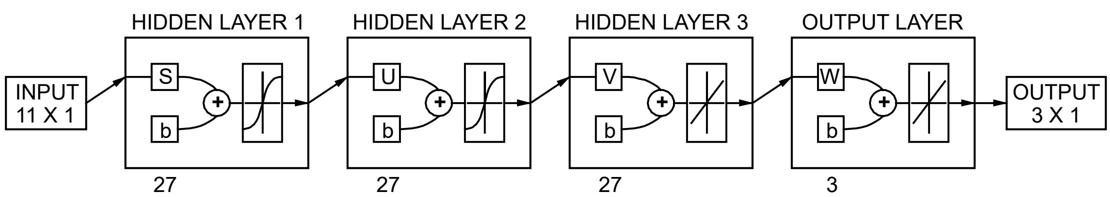

Figure 3. NN for prediction of nonlinear roll equation coefficients

The desired output matrix is also presented as equation (4). Index d indicates the desired value of these parameters.

$$\text{Output} = [A_d \;\; B_d \;\; C_d]^T \tag{4}$$

The output matrix of this network had three values: the moment of inertia, damping, and restoring coefficients of the roll motion equation. The provision of correct or desired data is important in NN training. In the following section, the computation of the desired values for the network is presented. The provision of the training data is made simpler and less costly by using a model-scale ship. Therefore, the use of dimensionless or scaled coefficients is preferable for network training. In this case, the trained network would also be usable for a real-size ship.

Moment of inertia coefficient

Coefficient A is the moment of inertia plus added moment of inertia, which is expressed as follows (Bhattacharyya, 1978):

$$A = I_{xx} + \delta I_{xx} \tag{5}$$

$$A = \Delta k_{xx}^2 + \Delta k'^2_{xx} = \Delta\left(k_{xx}^2 + k'^2_{xx}\right) = \Delta k''^2_{xx} \tag{6}$$

For a frigate ship, the experimental equation (7) is suggested (Bhattacharyya, 1978). The added moment of inertia depends on the encounter between wave frequency and motion frequency. The obtained value from the equation below is assumed to be the fixed initial value for all the inputs, and it is adjusted in the section *Nonlinear damping coefficient*, with some changes.

$$\left(\frac{K''_{xx}}{B}\right)^2 = 0.172\left[C_B C_u + 1.10 C_e\left(1 - C_B\right)\left(\frac{H_n}{d} - 2.2\right) + \frac{H_n^2}{B_u^2}\right] \tag{7}$$

$$H_n = D + \frac{A_n}{L_{pp}} \tag{8}$$

In this equation, the unit of the parameters with dimensions is the appropriate SI unit. The parameters are as follows:

B – total breath of the ship,
C_B – block coefficient,
C_u – total ship's deck area coefficient,
C_e – ship's deck area exposed to air coefficient,
d – ship's draft,
B_u – waterline breadth,
D – depth of the main deck,
A_n – the side area of the superstructure above the main deck.

Restoring moment coefficient

When the ship is inclined in the direction of the roll motion, a coupled moment between gravity and buoyancy is created, which tries to return the ship to the initial position. This moment is known as the restoring moment (Figure 4).

$$C_d x = \Delta\text{GZ}(x) \tag{9}$$

$$\Delta\text{GZ}(x) = c_1 x + c_2 x^2 + c_3 x^3 + c_4 x^4 + c_5 x^5 = C_d x \tag{10}$$

$$\Rightarrow C_d = c_1 + c_2 x + c_3 x^2 + c_4 x^3 + c_5 x^4 \tag{11}$$

The following figure shows the values of ΔGZ.

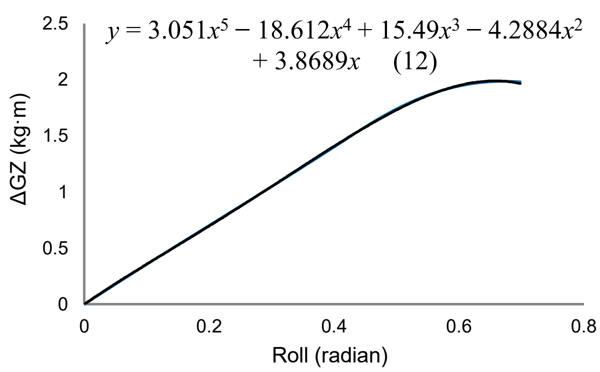

Figure 4. ΔGZ chart

Figure 4 shows the GZ curve of the ship under operational loading. This curve is variable for different values of trim and draft. Therefore, this curve can be drawn for a range of these variables, and the desired restoring coefficient (C_d) can be interpolated and calculated based on the network input. For the precision of Figure 4, a 40-degree range (0.7 radians) was considered.

Similarly to the inertia coefficient, the constant coefficients of this equation can also be scaled to the λ coefficient with the desired ratio. As was mentioned before, the dimensionless or scalable coefficients made the use of a model-scale ship instead of a real-size ship possible and reduced the computational volume. On the other hand, the trained network would be usable for the main ship.

Nonlinear damping coefficient

The desired value, for each input of the network for the damping coefficient, can be calculated by equation (13).

$$B_d = \frac{F - C_d x - A\ddot{x}}{\dot{x}} \quad (13)$$

The important point in the preparation of the training data is that a damping coefficient is a positive value, and its value should not be considerably larger than the mean value. If this coefficient is negative, or its absolute value is large, it means that the considered values for the restoring and inertial coefficient are incorrect. The current study shows that if the restoring moment is calculated precisely according to the section *Restoring moment coefficient*, by small adjustments in the value of the added mass coefficient, the damping coefficient value can be made proportionate to its surrounding points. An advantage of an NN is that it acts as a filter and does not create out-of-range data. The following steps must be taken to prepare the training data:

1. All the input values of coefficients should be calculated based on the equations in the section *Nonlinear roll artificial neural network structure*. Consider the constant value for the mass inertial coefficient, which is calculated according to the section *Moment of inertia coefficient*.
2. With a small change of about 5% in the constant added mass coefficient, the following considerations must be addressed:
   - The lowest number of points in which the damping coefficient is negative.
   - The range of damping coefficient changes is minimized for all points.

Neural network training

The deviation between the network output and the desired output is used to train the network, and the error function is calculated based on this deviation. The network weights must be set in such a way that the error function (Equation (14)) is minimized. Therefore, the weights are adjusted by the change in the reverse direction of the error function gradient. This method is called backpropagation. The following equations and schematic generally present the error backpropagation and weight adjustment (Jain, Mao, & Mohiuddin, 1996).

$$E = \frac{1}{2}\sum_{p=1}^{l}\left(d_p - z_p\right)^2 \quad (14)$$

$$\Delta\omega = -\eta\frac{\nabla E}{\nabla \omega} \quad (15)$$

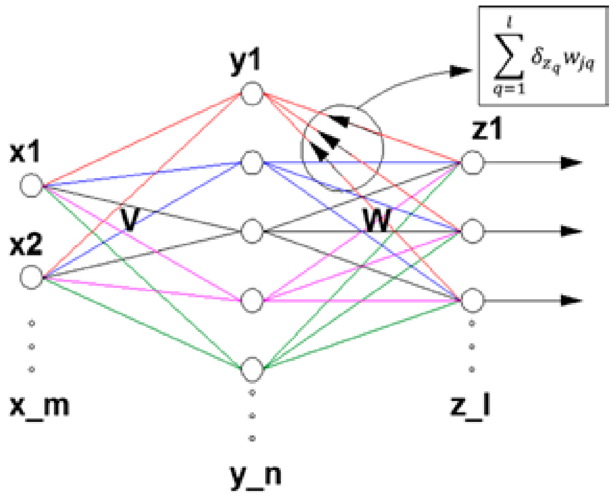

Figure 5. The error backpropagation method and weight adjustment

The equations of the weight adjustment of the output layers are as follows:

$$\Delta w_{ij} = -y_i \delta_{z_j} \eta \quad (16)$$

$$\delta_{z_j} = \left(d_j - z_j\right) f'\left(z_j\right) \quad (17)$$

In equation (14), d_p is the desired value, and z_p is the network output. The equations of the mid-layers are as follows:

$$\Delta v_{ij} = -x_i \delta_{y_j} \mu \quad (18)$$

$$\delta_{y_j} = f'\left(y_j\right)\sum_{q=1}^{l}\delta_{z_q} w_{jq} \quad (19)$$

μ and η are the training coefficients that lead the training, so that all the training samples undergo change, and the training for the last samples is better than the previous samples. These coefficients reduce the training percentage, which is calculated as the mean. The reduction in the training coefficients in the final stages of training leads to getting close to the objective. In the momentum method (Equation (20)), a weight adjustment is made based on the means of some of the latest samples.

$$\Delta\overline{W}_{ij}(t+1) = -\eta\frac{\partial E(t+1)}{\partial W_{ij}} + \alpha\Delta\overline{W}(t) \quad (20)$$

Simulation and validation

The simulation and training of the network were carried out in two phases. In the first phase, the network training was based on the test results in the IIHR laboratory at the American University of Iowa. The conducted tests were related to the roll decay, and the ship's model started moving at different speeds in a towing tank with an initial roll angle (Irvine, Longo, & Stern, 2004). This experiment was conducted for different speeds and initial rolling angles. In the current study, the ship's time-domain response was used. Regarding the fact that the oscillation was free and there were no waves, there were no roll exciting moments.

The RK4 method was used for solving the motion differential equation and the simulation of the roll motion. For the simulation, MATLAB Simulink software was used. The NN was placed in this signal diagram as a box and provided the equation coefficients based on the input response values. The differential equation was solved based on these coefficients. Figures 6 to 8 show the ship's roll response with respect to time. As seen, the simulated roll motion had good consistency with the test data.

For validation of the NN results, the maximum values of the rolling angle, the reduction amount in each oscillation, and the period of each swing were compared to the test results. These parameters are presented in Figure 9.

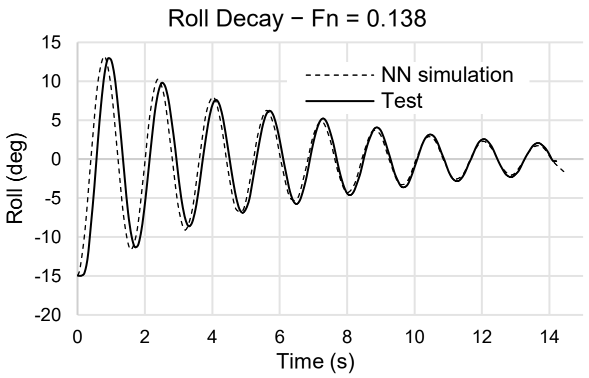

Figure 6. Roll motion simulation with a Froude number of 0.138

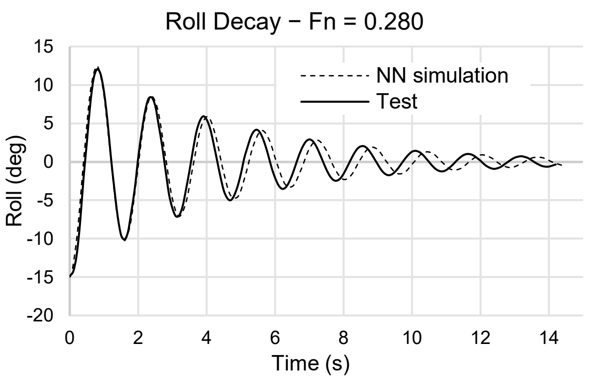

Figure 7. Roll motion simulation with a Froude number of 0.280

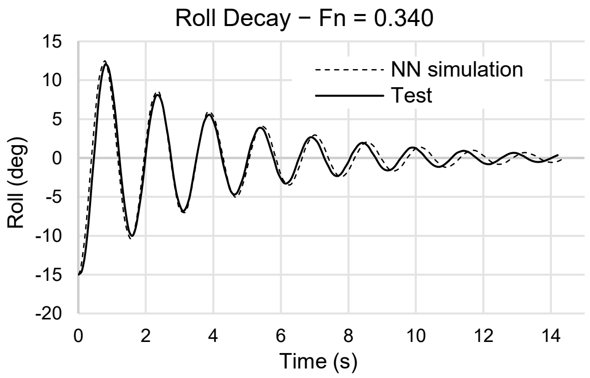

Figure 8. Roll motion simulation with a Froude number of 0.340

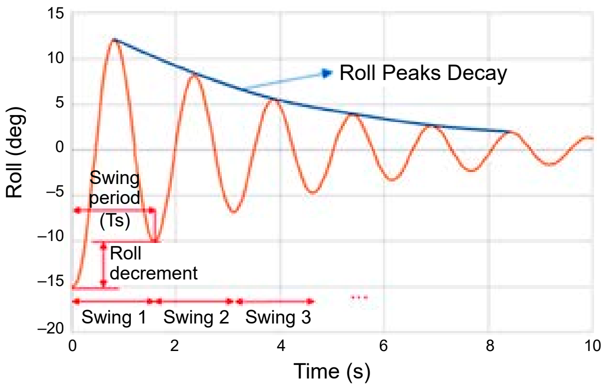

Figure 9. Roll motion validation parameters

The values of the roll peaks are presented in Figure 10. The accuracy of the peak values is essential in the simulation because in the control and roll stabilizer systems the primary control signal and the righting moment are generated based on the peak values. In addition to the peak values, the prediction of the corresponding time is important in the simulation. The deviation between the real times for peak occurrence and the simulation times caused amplification of the roll motion instead of stabilization. In Table 2, the error percentage of the roll motion validation parameters are presented.

In Figure 11, the roll decrement for each swing is presented. The value of roll decrement in each swing depends on the damping force. The test and simulation results are close to each other, meaning that the neural network correctly estimates the damping coefficients.

In the second phase, the network was trained based on the ship's response data in the irregular waves. The initial weights' conditions in the network were based on the trained neural network in the previous phase. The wave conditions, ship's speed, and heading angle were based on Table 3. These data were obtained based on numerical simulation (Mousavi, Khoogar, & Ghassemi, 2020). Numerical

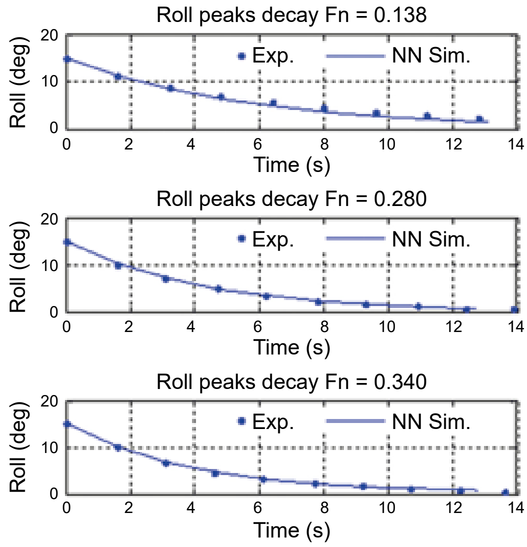

Figure 10. Roll peaks decay

Table 2. The mean error of simulation, compared to the test results, for the regular response

Froude No.	Average errors			
	Roll peaks	Roll peaks time (for 8 swings)	Swing period	Roll decrement
0.138	14.67%	0.2 s	2.36%	12.59%
0.280	4.56%	0.07 s	3.39%	3.08%
0.340	7.24%	0.1 s	5.22%	5.02%

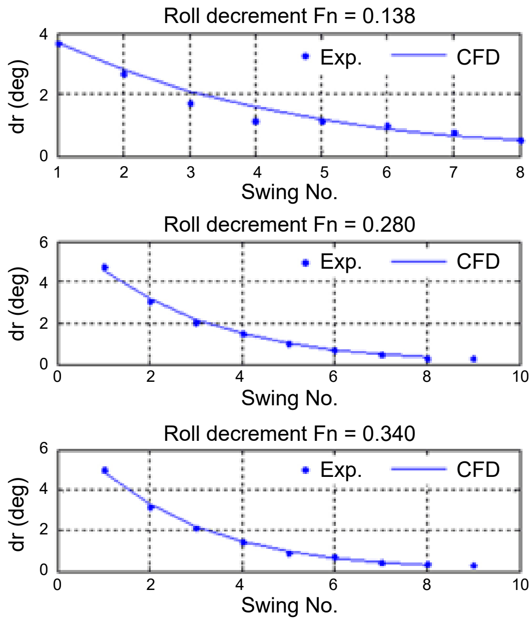

Figure 11. Roll decrement

Table 3. Simulation irregular condition

Heading speed (knot)	Heading angle (degree)	Irregular wave parameter	
		Significant wave height (m)	Modal period (s)
20	10	3.28	9.146

simulation has been verified in this reference, but the numerical result accuracy is not important, and the main goal of this section is to show that the trained neural network can trace the roll motion and can predict the dynamic coefficient in irregular waves. In practical use, the NN, training will be modified using the error between the ship's real motion and the predicted motion (NN results).

Figure 12 shows the ship's roll time history response in irregular waves. Figure 13 shows the exciting moment applied on the ship in the direction of roll with respect to time. Figures 14 and 15 show the ship's pitch and heave time response. Figure 16 shows the network training error. The network reached an error of lower than $1 \cdot e^{-5}$ after 1115 calculation periods. Figure 17 shows the downward gradient for the weights and coefficient of momentum.

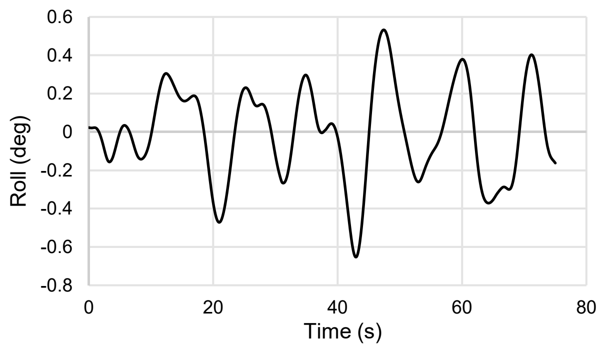

Figure 12. Ship's roll time history

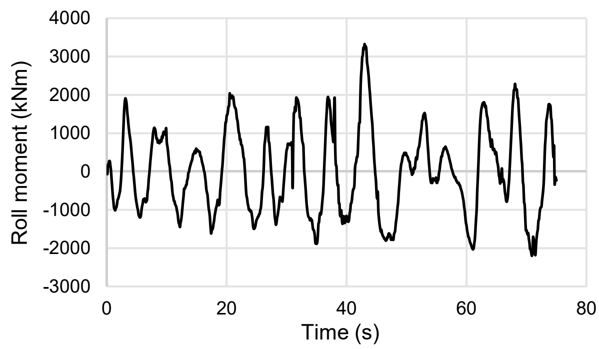

Figure 13. Ship's roll moment time history

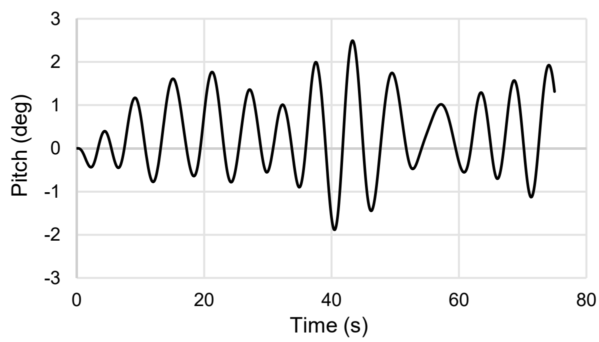

Figure 14. Ship's pitch motion time history

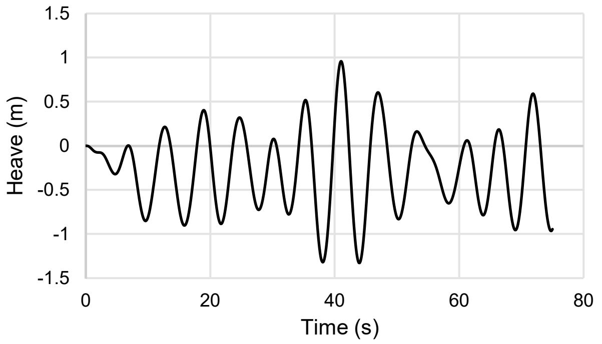

Figure 15. Ship's heave motion time history

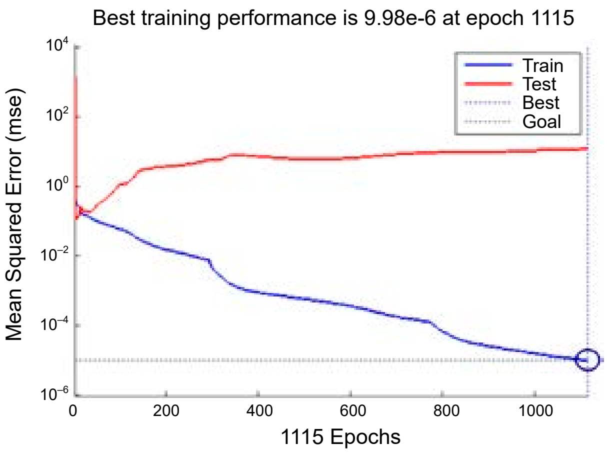

Figure 16. Network training error

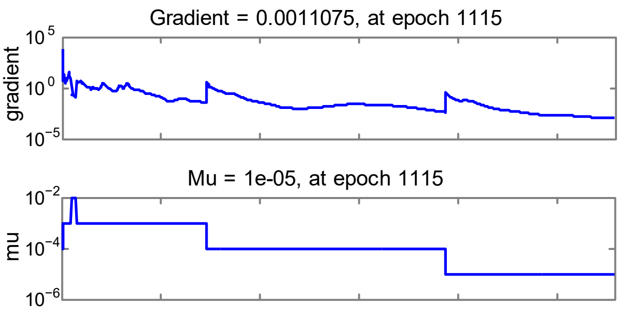

Figure 17. Error function gradient and momentum coefficient

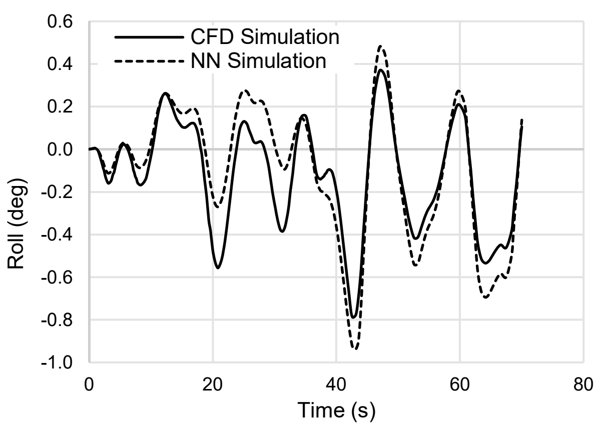

Figure 18. Comparison between the results of the NN and the CFD simulation of roll motion

The results of the roll motion simulation were compared to the initial results in Figure 18. The results of the NN simulation had a 20% average error compared to the numerical solution results.

Conclusions

In the current study, the definition of the nonlinear roll equation with consideration for the degrees of freedom of heave and pitch was carried out using a feed-forward artificial NN. The first phase was based on the roll decay test, and the second phase was based on the data obtained from CFD simulation in irregular and oblique waves. Preparation of the training data is very important, and these data must have an appropriate range so that the training is carried out correctly. Empirical equations were used in the current study for controlling the range of the coefficients.

In many cases, testing the ship in an oblique wave with heading angles is not possible since the tests are time-consuming and costly. Also, the simulation with the CFD method is difficult and complicated. In this study, after the NN initial training based on the roll decay test, the network was used for training and simulation in irregular and oblique waves. The network was able to simulate to a good approximation and was not sensitive to the new conditions. The NN was stable when the environmental conditions suddenly changed, and it could be used as a robust system.

In the current study, the pitch and heave motions were among the inputs of the NN, and their effects on the damping coefficient were considered. The NN involves nonlinear mapping, and precise achievement of this mapping is only viable through more accurate input variables that are more consistent with reality.

The NN itself acts as a powerful filter for the elimination of the out-of-range data, and it prevents divergence. The NN, in addition to having acceptable accuracy, has low sensitivity to condition changes. Another advantage of the NN is its high speed, which is an effective factor in controlling motion in waves and designing control systems.

References

1. Alarçin, F. (2007) Internal model control using neural network for ship roll stabilization. *Journal of Marine Science and Technology* 15, 2, pp. 141–147.
2. Awad, T., Elgohary, M.A. & Mohamed, T.E. (2018) Ship roll damping via direct inverse neural network control system. *Alexandria Engineering Journal* 57, 4, pp. 2951–2960.

3. Bhattacharyya, R. (1978) *Dynamics of marine vehicles*. New York: John Wiley & Sons.
4. Ghassemi, H., Dadmarzi, F., Ghadimi, P. & Ommani, B. (2010) Neural network-PID controller for roll fin stabilizer. *Polish Maritime Research* 17(2), pp. 23–28.
5. Hou, X.-R., Zou, Z.-J. & Liu, C. (2018) Nonparametric identification of nonlinear ship roll motion by using the motion response in irregular waves. *Applied Ocean Research* 73, pp. 88–99.
6. Irvine, M., Longo, J. & Stern, F. (2004) *Towing Tank Tests for Surface Combatant for Free Roll Decay and Coupled Pitch and Heave Motions*. Proceedings of the 25th ONR Symposium on Naval Hydrodynamics, St Johns, Canada.
7. Jain, A.K., Mao, J. & Mohiuddin, K.M. (1996) Artificial neural networks: a tutorial. *Computer* 29, 3, pp. 31–44.
8. Lewis, E.V. (1989) *Principles of Naval Architecture*. 2nd edition. SNAME.
9. Mahfouz, A.B. (2004) Identification of the nonlinear ship rolling motion equation using the measured response at sea. *Ocean Engineering* 31, 17–18, pp. 2139–2156.
10. Mousavi, S.M., Khoogar, A.R. & Ghassemi, H. (2020) Time Domain Simulation of Ship Motion in Irregular Oblique Waves. *Journal of Applied Fluid Mechanics* 13(2), pp. 549–559.
11. Oskin, D.A., Dyda, A.A. & Markin, V.E. (2013) Neural network identification of marine ship dynamics. *IFAC Proceedings Volumes* 46, 33, pp. 191–196.
12. Pérez, T. & Blanke, M. (2002) *Simulation of Ship Motion in Seaway*. Tech. rep EE02037.
13. Xing, Z. & McCue, L. (2010) Modeling ship equations of roll motion using neural networks. *Naval Engineers Journal* 122, 3, pp. 49–60.

Cite as: Mousavi, S.M.M., Khoogar, A.R., Ghassemi, H. (2022) Ship nonlinear roll motion identification using artificial neural network. *Scientific Journals of the Maritime University of Szczecin, Zeszyty Naukowe Akademii Morskiej w Szczecinie* 72 (144), 65–74.