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Prediction of Semi-Submersible Floating Platform Responses to Ocean Waves Using Artificial Neural Networks

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Abstract

Accurate prediction of wave-induced motions is essential for the design and safe operation of marine and offshore structures. Among these motions, heave and pitch significantly affect structural performance and operational safety. Conventional hydrodynamic methods are often computationally expensive and unsuitable for real-time applications. This study presents a prediction framework based on a Generalized Feedforward Artificial Neural Network (GFANN) to estimate the heave and pitch responses of a semi-submersible platform under various wave conditions. A hydrodynamic dataset generated using strip theory, covering different vessel speeds and wave headings (0°–180°), was used for training and validation. The proposed model accurately predicts vessel motions under unseen conditions while requiring significantly less computational effort than conventional simulations. The results demonstrate the capability of GFANN to capture nonlinear response behavior and support real-time applications such as operational planning, digital twins, and intelligent monitoring in marine engineering.

Keywords: Artificial intelligence, Machine learning, Generalized feedforward neural network, Ship motion prediction, Heave response, Pitch response.

1 | Introduction

The prediction of marine vessel motions in waves is one of the fundamental challenges in naval architecture and offshore engineering. A vessel operating in a marine environment is continuously exposed to external excitations generated by waves, wind, and current, resulting in complex dynamic responses. These responses are commonly described by Six Degrees of Freedom (6-DOF), including three translational motions (surge,

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sway, and heave) and three rotational motions (roll, pitch, and yaw). Accurate estimation of these motions is essential because they directly affect vessel safety, structural integrity, passenger comfort, propulsion efficiency, operational capability, and the performance of onboard systems [1], [2].

Among different ship motions, vertical-plane motions, particularly heave and pitch, have attracted considerable attention due to their significant influence on the seakeeping behavior of high-speed and semi-displacement vessels. Excessive heave and pitch amplitudes can increase vertical accelerations, induce uncomfortable operating conditions, increase the probability of bow and stern slamming, cause deck wetness, reduce crew performance, and impose additional dynamic loads on the hull structure and marine equipment. Therefore, reliable prediction of these coupled motions is a key requirement in vessel design, performance evaluation, and operational decision-making [1], [2].

Semi-displacement vessels represent an important category of marine craft that operate between conventional displacement ships and fully planing vessels. Unlike pure displacement vessels, where the weight is primarily supported by hydrostatic buoyancy, semi-displacement vessels benefit from both hydrostatic forces and hydrodynamic lift generated at higher speeds. This operating regime provides a compromise between fuel efficiency, speed capability, and maneuverability, making semi-displacement vessels widely used in military, patrol, rescue, passenger transportation, and recreational applications [3], [4].

However, the hydrodynamic behavior of semi-displacement vessels is highly nonlinear because of the interaction between hull geometry, forward speed, wave characteristics, and heading angle. As the vessel speed increases, coupling between vertical motions becomes stronger, and accurate prediction of heave–pitch responses becomes more challenging. In particular, the dynamic coupling between heave and pitch plays a critical role in determining operational limitations under severe sea states [5], [6].

Traditionally, ship motion responses have been investigated using three major approaches: theoretical/numerical methods, model experiments, and full-scale sea trials. Experimental methods provide valuable information but require significant financial and time resources. Full-scale measurements, although highly reliable, are usually limited by environmental availability and operational constraints. Therefore, computational approaches have become essential tools for preliminary design and performance assessment [7], [8].

Among numerical approaches, potential-flow-based methods such as strip theory have been widely used for ship seakeeping analysis due to their computational efficiency and reasonable accuracy for many practical applications. Strip theory divides the ship hull into a series of two-dimensional sections and estimates hydrodynamic coefficients based on sectional analysis. However, these methods may require repeated simulations for different combinations of speed, wave frequency, and wave heading angle, leading to considerable computational effort when large design spaces are investigated [9], [10].

More advanced numerical techniques such as Computational Fluid Dynamics (CFD) have also been employed to predict ship motions and wave–structure interactions. Although CFD methods provide detailed flow-field information and can capture nonlinear phenomena more accurately, their high computational cost limits their application for real-time prediction and extensive parametric studies. Therefore, developing fast and reliable predictive models remains an important research objective in marine engineering [10], [11].

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have introduced new opportunities for solving complex nonlinear engineering problems. Data-driven models, particularly Artificial Neural Networks (ANNs), have demonstrated strong capabilities in approximating nonlinear relationships between input parameters and system responses. Unlike traditional analytical models, neural networks can learn hidden patterns directly from available datasets and provide rapid predictions after the training process [2].

In marine engineering, AI techniques have been increasingly applied for ship resistance prediction, maneuvering analysis, structural health monitoring, and seakeeping performance evaluation. The ability of

ANN models to provide near-real-time predictions makes them attractive for applications such as intelligent navigation systems, digital twins, autonomous vessels, and operational decision-support frameworks [1].

Although several studies have investigated the application of neural networks for predicting ship responses, limited research has focused on the prediction of coupled heave and pitch motions of semi-displacement vessels over a wide range of operational conditions. Most existing studies have concentrated on conventional displacement ships or specific loading conditions, while the nonlinear behavior of semi-displacement craft remains relatively less explored [12].

Therefore, the present study develops a Generalized Feedforward Artificial Neural Network (GFANN) model for predicting the coupled heave and pitch responses of a semi-displacement vessel subjected to irregular waves. The hydrodynamic response database is generated using strip theory calculations for different vessel speeds and wave encounter angles. The developed neural network is trained and validated using the generated dataset, and its prediction capability is evaluated by comparing ANN outputs with numerical hydrodynamic results [13].

The main objective of this research is to establish an efficient data-driven framework capable of reducing computational time while maintaining acceptable prediction accuracy. The proposed methodology provides a practical approach for rapid seakeeping assessment and can contribute to future intelligent marine systems and real-time vessel performance monitoring [9].

Recent advances in AI, ML, and data-driven modeling have opened new opportunities for maritime engineering applications. ANNs, in particular, have demonstrated strong capabilities in capturing complex nonlinear relationships and approximating highly dynamic systems. Their ability to learn directly from data makes them promising tools for predicting vessel responses under varying environmental and operational conditions [14].

In this study, a GFANN is developed to predict the heave and pitch motions of a semi-displacement vessel subjected to wave excitation. Hydrodynamic response data are generated using strip theory for different vessel speeds and wave heading angles ranging from 0° to 180°. The generated dataset is employed to train and validate the neural network model. The predictive capability of the proposed framework is subsequently assessed through comparison with conventional hydrodynamic calculations. The results demonstrate the effectiveness of the proposed data-driven approach in accurately estimating vessel motions while significantly reducing computational effort, highlighting its potential for real-time maritime applications and intelligent decision-support systems [15].

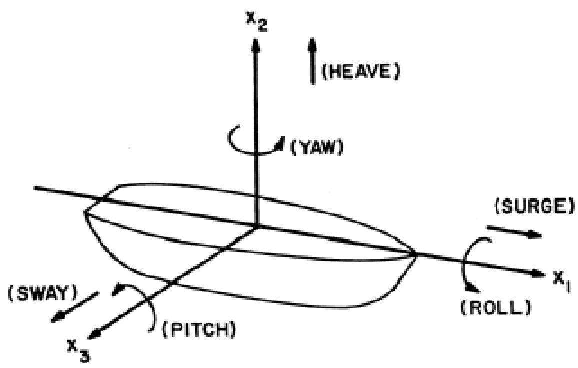

Fig. 1. 6-DOF of a marine vessel.

Ship motions induced by ocean waves have a significant impact on passenger comfort, vessel operability, structural safety, and crew performance. Consequently, reliable prediction of vessel motions under realistic sea conditions is an essential requirement during the design and operational stages of marine systems. Accurate estimation of seakeeping characteristics enables naval architects to evaluate vessel performance, optimize hull designs, and ensure compliance with safety and operational requirements.

As vessel speed increases, the dynamic behavior of marine craft becomes increasingly complex. While low-speed vessels are primarily characterized by horizontal-plane motions, namely surge, sway, and yaw, higher-speed vessels experience more pronounced vertical-plane motions such as heave, pitch, and roll. These motions introduce additional challenges in vessel control, maneuverability, and operational stability. In particular, the coupling between heave and pitch motions is more pronounced in semi-displacement and high-speed vessels due to their hydrodynamic characteristics and operating conditions.

Large-amplitude heave and pitch responses can lead to several adverse effects, including increased vertical accelerations, higher relative motions between the vessel and the surrounding water surface, increased probability of slamming events, deck wetness, reduced crew efficiency, passenger discomfort, and potential damage to onboard equipment and structural components. Therefore, accurate prediction and mitigation of these motions have become critical objectives in modern ship design and seakeeping analysis.

Traditionally, vessel seakeeping performance has been evaluated using three principal approaches: numerical simulations, model-scale experiments, and full-scale sea trials. Among these methods, computational approaches have gained widespread acceptance because of their lower cost, greater flexibility, and accessibility compared with experimental investigations. Nevertheless, many conventional numerical methods remain computationally demanding and often rely on simplifying assumptions that may limit their ability to capture highly nonlinear hydrodynamic phenomena. These limitations have motivated the development of alternative predictive techniques capable of providing rapid and reliable estimates of vessel responses.

In recent years, AI and ML techniques have emerged as powerful tools for modeling complex engineering systems. ANNs are particularly attractive because they can learn nonlinear relationships directly from data without requiring explicit mathematical representations of the underlying physical processes. Such capabilities make ANN-based approaches promising candidates for seakeeping analysis, motion prediction, and intelligent maritime decision-support systems.

Although extensive research has been conducted on the seakeeping performance of various vessel types, relatively limited attention has been devoted to the application of neural-network-based approaches for predicting the hydrodynamic responses of semi-displacement vessels. Early studies demonstrated the potential of ANNs in ship-motion prediction. For example, Hadara and Xu [16] developed ANN-based models for coupled heave and pitch motions in random wave environments, while subsequent investigations employed neural networks to evaluate the seakeeping performance of cargo vessels under different loading conditions. Despite these efforts, the application of data-driven techniques to semi-displacement craft remains relatively unexplored, particularly for coupled heave–pitch response prediction across a broad range of operational conditions.

Accordingly, the present study investigates the hydrodynamic behavior of a representative semi-displacement vessel using a GFANN. Motion-response data are generated based on strip-theory calculations for vessel speeds ranging from 0 to 27 knots and wave-heading angles between 0° and 180°. Simulations are performed under Sea State 5 conditions using the Bretschneider wave spectrum and short-crested irregular waves. The generated database is subsequently employed to train and validate the neural-network model for predicting coupled heave and pitch responses. The proposed framework aims to provide a computationally efficient and accurate alternative to conventional hydrodynamic analysis methods while supporting future developments in intelligent ship-performance prediction and real-time maritime decision-making systems.

Table 1. Principal particulars of the semi-displacement vessel.

Parameter	Value
Overall Length, LOA (m)	57.0
Length Between Perpendiculars, LBP (m)	48.7
Beam (m)	8.5
Depth (m)	4.2
Draft (m)	2.6
Displacement (tonnes)	562.5
Radius of gyration about the transverse axis (m)	0.225L

The principal dimensions and hydrostatic characteristics of the semi-displacement vessel considered in this study are presented in *Table 1*. To evaluate the seakeeping performance of the vessel, the strip theory approach was employed to calculate the hydrodynamic responses. In addition, the sectional hydrodynamic coefficients were determined using the conformal mapping technique, which provides an efficient representation of the hull geometry for motion analysis.

Considering the coupled nature of vertical-plane ship motions, the heave and pitch responses in irregular seas were modeled through two coupled second-order differential equations. These equations account for the effects of added mass, hydrodynamic damping, hydrostatic restoring forces, and wave excitation loads. The resulting mathematical model forms the basis for generating the response database used in the development and training of the ANNs model.

Accordingly, the coupled heave–pitch dynamics of the vessel in a realistic sea environment can be expressed by the following second-order coupled equations:

$$(m + a_{33})\ddot{x}_3 + b_{33}\dot{x}_3 + c_{33}x_3 + a_{35}\ddot{x}_5 + b_{35}\dot{x}_5 + c_{35}x_5 = f_3(t). \tag{1}$$

$$a_{53}\ddot{x}_3 + b_{53}\dot{x}_3 + c_{53}x_3 + (I_{55} + a_{55})\ddot{x}_5 + b_{55}\dot{x}_5 + c_{55}x_5 = f_5(t), \tag{2}$$

where (m) represents the vessel mass and (I_{yy}) denotes the mass moment of inertia of the vessel about the transverse axis passing through the center of gravity. The terms (A_{33}) and (A_{55}) represent the added mass and added moment of inertia coefficients associated with heave and pitch motions, respectively. The parameters (B_{33}) and (B_{55}) denote the corresponding hydrodynamic damping coefficients, while (C_{33}) and (C_{55}) represent the hydrostatic restoring coefficients. The terms (F_{3t}) and (M_{5t}) are the wave excitation force and moment acting on the vessel in heave and pitch modes, respectively [5], [8].

These hydrodynamic coefficients describe the interaction between the vessel and the surrounding fluid and play a fundamental role in determining the seakeeping characteristics of the semi-displacement vessel. Accurate estimation of these parameters is essential for generating reliable training data for the ANNs-based prediction model.

2 | Artificial Neural Network Model

In this study, a GFANN model is developed to predict the seakeeping responses of the semi-displacement vessel. ANNs are powerful data-driven modeling tools capable of identifying complex nonlinear relationships between input variables and system responses without requiring an explicit mathematical formulation of the physical process.

The proposed GFFN model is trained using the Levenberg–Marquardt (LM) optimization algorithm, which is widely recognized as an efficient and fast training approach for nonlinear regression problems. The hyperbolic tangent sigmoid (tanh) activation function is employed within the hidden layers to provide nonlinear mapping capability and improve the learning performance of the network.

The input parameters of the neural network consist of the vessel forward speed and wave encounter angle, which represent the main operational and environmental parameters affecting the hydrodynamic behavior of the vessel. The outputs of the network are the corresponding wave-induced motion responses, including coupled heave and pitch motions of the semi-displacement vessel.

The training dataset is generated from the numerical seakeeping analysis based on strip theory calculations under various operating conditions. The neural network learns the relationship between vessel operating parameters and motion responses and subsequently provides predictions for conditions that are not included in the training dataset.

The predicted heave and pitch responses obtained from the developed GFFN model are presented in *Figs. 2* and *3*. These results are used to evaluate the accuracy and generalization capability of the proposed AI -based prediction framework.

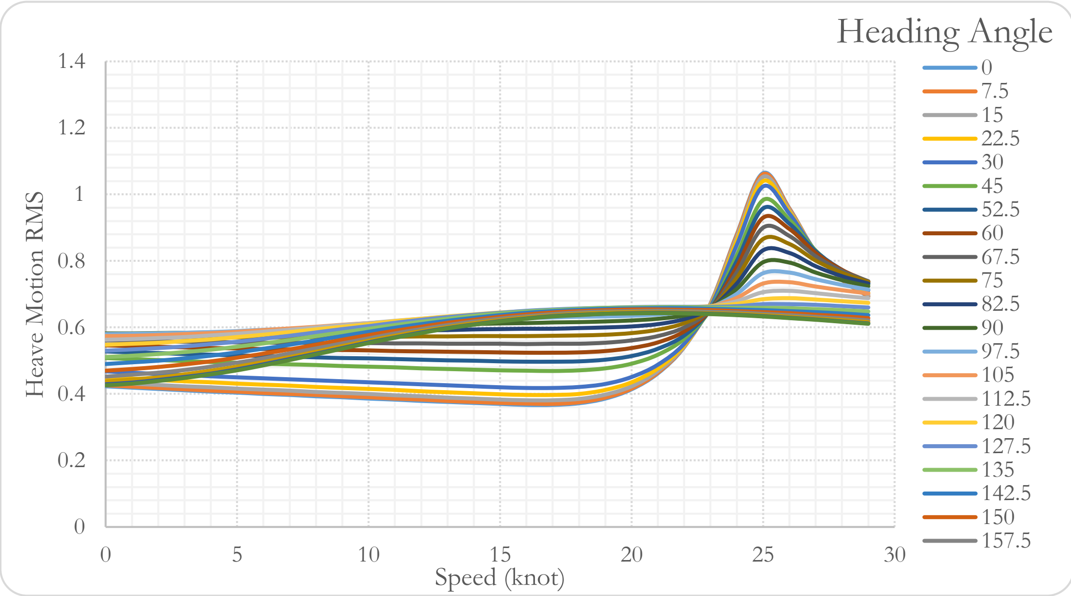

Fig. 2. Heave response of the vessel under different speeds and wave heading angles.

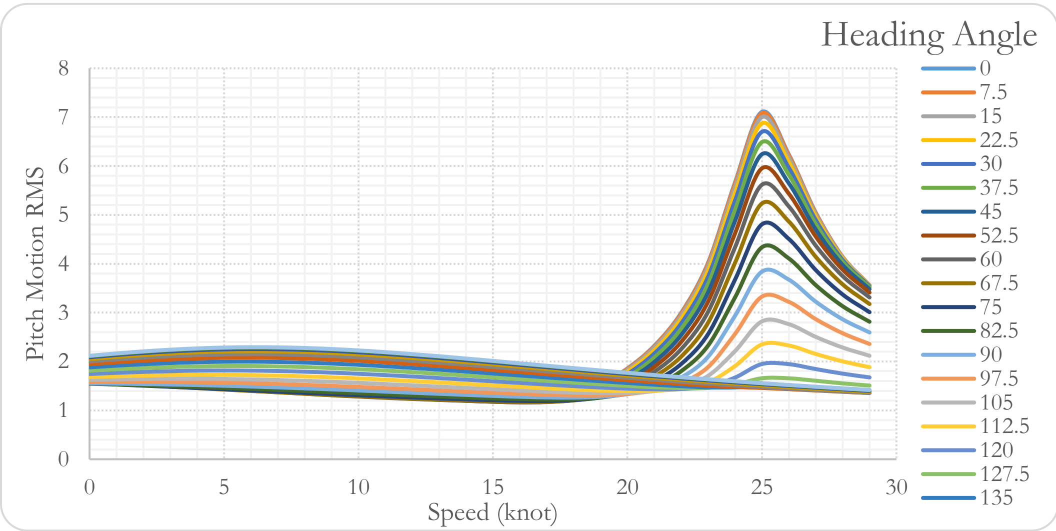

Fig. 3. Pitch response of the vessel under different speeds and wave heading angles.

2.1 | Generalized Feedforward Neural Networks

Generalized Feedforward Neural Networks (GFFNs) are a class of Multilayer Perceptron (MLP) neural networks in which the connections between neurons are not restricted to adjacent layers and may skip one or more intermediate layers. Although conventional MLP architectures are theoretically capable of solving a wide range of nonlinear approximation problems, GFFN structures can provide improved computational efficiency and faster convergence in practical applications.

In comparison with standard MLP networks, GFFNs generally require fewer training iterations and demonstrate enhanced learning capability under similar computational conditions. This advantage makes

GFFNs suitable for complex engineering problems involving nonlinear relationships between input variables and system responses, such as ship motion prediction under wave excitation [9].

In the present study, the GFFN model is employed to establish a nonlinear mapping between the vessel operating conditions and its hydrodynamic responses. The vessel speed and wave encounter angle are considered as input variables, while the predicted heave and pitch motions are used as network outputs.

2.2 | Optimization of Transfer Function and Training Algorithm

To achieve accurate prediction of the vessel responses obtained from strip theory calculations, different combinations of activation functions and training algorithms were investigated. The performance of sigmoid (Si) and hyperbolic tangent sigmoid (T) transfer functions was evaluated in combination with several training algorithms, including Steepest Descent (S), Momentum (M), Conjugate Gradient (C), Levenberg–Marquardt (L), Quick Propagation (Q), and Delta-Bar-Delta (D).

The optimal configuration was selected based on the minimum Mean Squared Error (MSE) obtained during the training process. As presented in *Table 2*, the combination of the hyperbolic tangent sigmoid transfer function and the Levenberg–Marquardt training algorithm provided the lowest prediction error. Therefore, this combination was selected as the optimal network configuration for predicting the coupled heave and pitch responses of the semi-displacement vessel.

Table 2. Selection of the optimal transfer function and training algorithm.

Transfer Function	Training Algorithm	MSE
T	S	0.217586
T	M	0.216737
T	C	0.193799
T	L	0.096175
T	Q	0.217487
T	D	0.197498
Si	S	0.872285
Si	M	0.872033
Si	C	0.761514
Si	L	0.130789
Si	Q	0.872274
Si	D	0.866937

2.3 | Determination of the Optimal Number of Hidden Layers

After selecting the appropriate transfer function and training algorithm, the optimal network architecture was determined to improve prediction accuracy while minimizing computational cost. For this purpose, several GFFN models with different numbers of hidden layers were trained and evaluated.

The obtained results indicate that the network configuration containing four hidden layers achieved the minimum MSE and was therefore selected as the optimal architecture (*Fig. 5*). Furthermore, each hidden layer consisted of six neurons, providing an appropriate balance between model complexity and generalization capability.

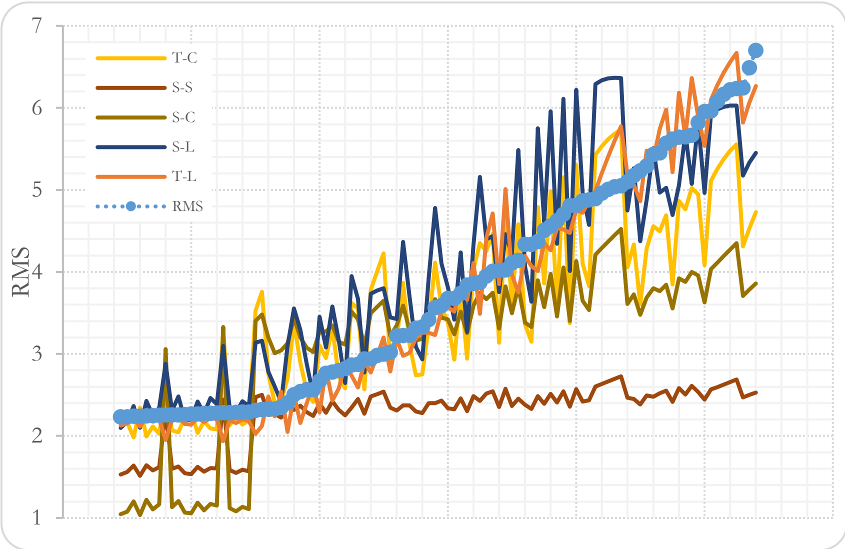

Fig. 4. Selection of the optimal transfer function and training algorithm.

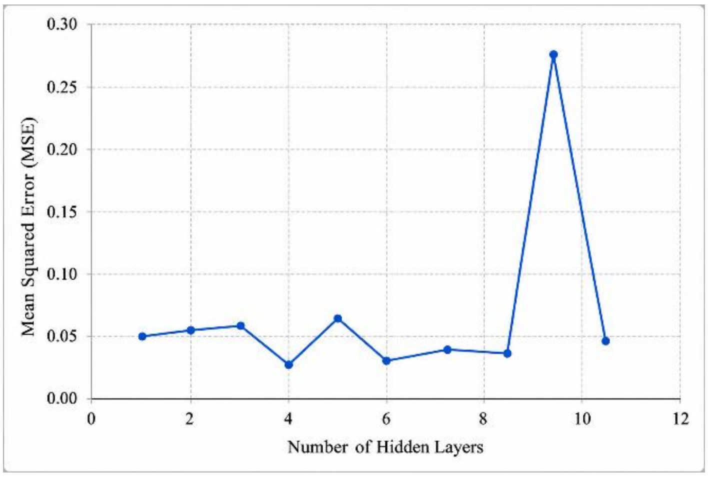

Fig. 5. Selection of the optimal number of hidden layers.

2.4 | Neural Network Architecture

Based on the optimization results obtained from the previous sections, the final architecture of the developed GFANN was determined. The selected network structure consists of the following components:

I. Input layer: The input layer contains two neurons representing the main operational and environmental parameters, including vessel forward speed and wave encounter angle.

II. Hidden layers: The network consists of four hidden layers, where each hidden layer contains six neurons. This structure was selected based on the minimum MSE criterion to achieve an appropriate balance between prediction accuracy and computational efficiency.

III. Output layer: The output layer provides the predicted hydrodynamic responses of the semi-displacement vessel, including the coupled heave and pitch motions.

The final architecture of the developed GFFN model is illustrated in *Fig. 6*. This configuration enables the network to learn the nonlinear relationship between wave excitation conditions and vessel motion responses.

3 | Results and Discussion

In this study, the optimized GFANN model was trained using the hyperbolic tangent sigmoid activation function and the Levenberg–Marquardt training algorithm. The vessel forward speed and wave encounter angle were considered as input variables, while the coupled heave and pitch responses obtained from strip theory calculations were used as target outputs. The generated dataset was divided into training, validation, and testing subsets to evaluate the learning capability and generalization performance of the proposed neural network model. The training performance of the developed GFFN model is presented in *Figs. 7* and *8*. These results demonstrate the convergence behavior of the network during the learning process and indicate the capability of the proposed model to approximate the nonlinear relationship between operational conditions and vessel motion responses. The achieved prediction accuracy confirms that the optimized GFFN structure can effectively reproduce the hydrodynamic behavior of the semi-displacement vessel under different wave conditions. The developed model provides a computationally efficient alternative to conventional numerical simulations and can be applied for the rapid prediction of ship motions in marine engineering applications.

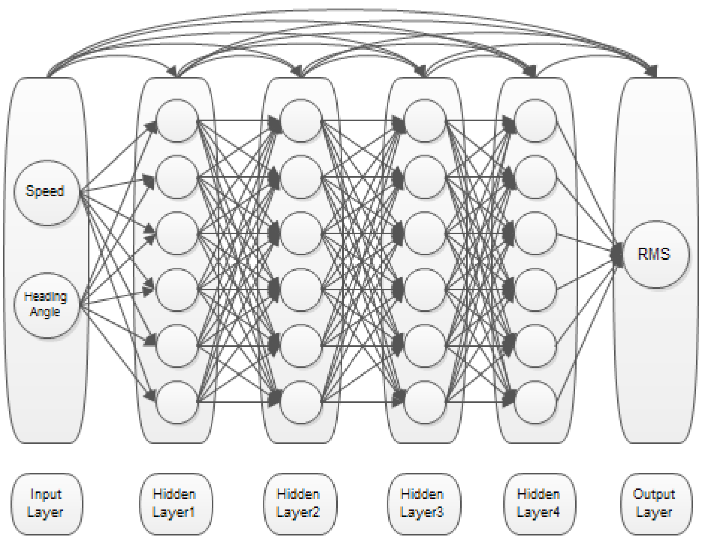

Fig. 6. Architecture of the developed ANNs.

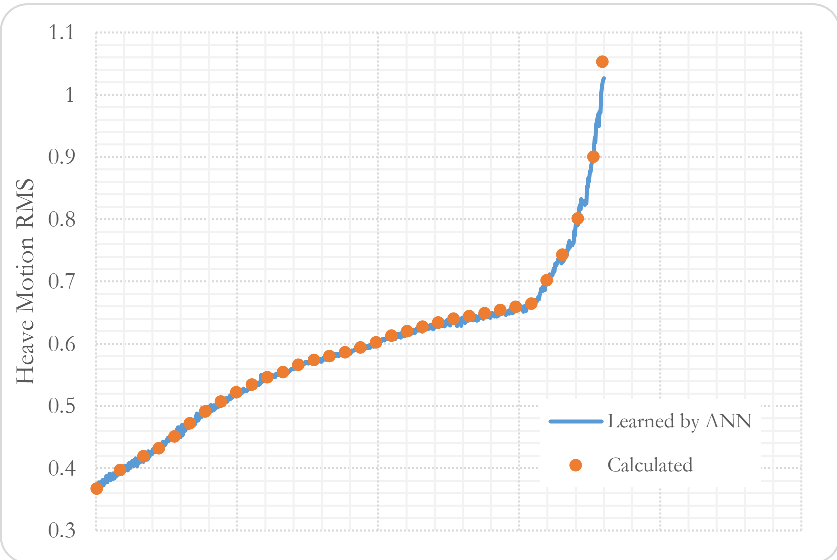

Fig. 7. Training performance of the neural network for the heave response prediction.

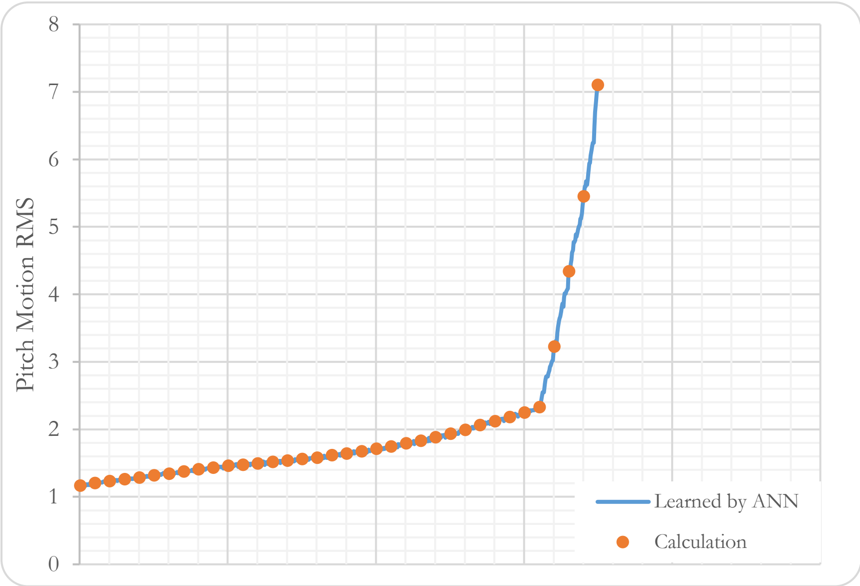

Fig. 8. Training performance of the neural network for pitch response prediction.

After validating the training performance of the developed neural network model against the numerical data obtained from strip theory calculations, the capability of the proposed GFFN model for predicting vessel responses under unknown operating conditions was investigated.

For this purpose, the trained network was employed to estimate the coupled heave and pitch responses at vessel speeds of 28 and 29 knots. These operating conditions were intentionally excluded from the training dataset in order to evaluate the generalization ability of the proposed model. The predicted results obtained from the neural network were compared with the corresponding hydrodynamic calculations, and the comparison results are presented in *Figs. 9* and *10*.

The results indicate that the predicted responses generated by the GFFN model closely follow the trends and variations of the numerical solutions. The network successfully captures the nonlinear relationship between vessel speed, wave encounter angle, and motion responses, even for conditions that were not included during the training process.

The good agreement between the ANN predictions and the conventional hydrodynamic calculations demonstrates the reliability and robustness of the proposed data-driven approach. Therefore, the developed GFFN model can be considered as an efficient predictive tool for rapid estimation of wave-induced heave and pitch motions of semi-displacement vessels, reducing the computational time required for repeated seakeeping analyses.

4 | Conclusion

In this study, a GFANN-based framework was developed to predict the coupled heave and pitch responses of a semi-displacement vessel under wave excitation. The neural network model was trained using hydrodynamic data obtained from strip theory calculations for different vessel speeds and wave encounter angles.

Several combinations of activation functions and training algorithms were investigated to determine the optimal network configuration. The results demonstrated that the combination of the hyperbolic tangent sigmoid activation function and the Levenberg–Marquardt training algorithm provided the best prediction performance with the lowest MSE. The selected network architecture was able to successfully learn the nonlinear relationship between vessel operating conditions and wave-induced motion responses.

The validation results showed that the predicted heave and pitch responses obtained from the developed GFFN model were in good agreement with the numerical calculations. Furthermore, the network demonstrated satisfactory generalization capability by accurately predicting vessel responses for operating conditions that were not included in the training dataset.

The results indicate that, when reliable and representative training data are available, ANNs can serve as efficient data-driven tools for predicting the seakeeping performance of marine vessels. The proposed approach can significantly reduce computational time compared with conventional numerical simulations and may provide a practical alternative for rapid performance assessment during vessel design and operational analysis.

Although model tests and full-scale sea trials remain important methods for final validation, the developed ANN-based framework can be considered as a complementary intelligent prediction tool for preliminary design studies, real-time monitoring systems, and future digital twin applications in marine engineering.

Conflict of Interest

The authors report no conflicts of interest related to this work.

Data Availability

All relevant data are presented in this manuscript.

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