Prediction of Parametric Roll Resonance by Multilayer Perceptron Neural Network

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ABSTRACT

Parametric roll resonance is a ship stability related phenomenon that generates sudden large amplitude oscillations up to 30-40 degrees of roll. This can cause severe damage, and it can put the crew in serious danger. The need for a parametric rolling real time prediction system has been acknowledged in the last few years. This work proposes a prediction system based on a multilayer perceptron (MP) neural network. The training and testing of the MP network is accomplished by feeding it with simulated data of a three degrees-of-freedom nonlinear model of a fishing vessel. The neural network is shown to be capable of forecasting the ship's roll motion in realistic scenarios.

KEY WORDS: parametric roll; prediction systems; artificial neural networks; fishing vessels.

INTRODUCTION

Parametric roll resonance is a well known phenomenon that has gathered great attention in the last years due to the real threat suffered by container ships in common passage conditions, which were generally considered of no danger. The resonance is most likely to happen when the ship is sailing in head or stern seas under some specific conditions as: the wave encounter frequency is approximately twice the ship's natural roll frequency; the wavelength is almost equal to the ship length; the wave amplitude is larger than a ship dependent threshold. When these conditions are fulfilled, the periodic alternation of wave crests and troughs amidships brings about dramatic changes in ship transverse stability, which in turn determines a sudden and quick growth of roll oscillations. The extreme roll motion can lead to ship structural and cargo damage, it can determine risky situations for the crew and, in the worst cases, can lead to capsizing.

The susceptibility of a ship to develop parametric roll is determined by the amplitude of the heeling arm variations, which depend on the hull form. Modern container carriers are particularly prone to parametric roll resonance due to their hull shapes – large bow flare, overhanging stern, wall-sided midship sections – which are designed to achieve an optimal trade-off between high service speed and maximum container payload above deck (Shin et al., 2004, France et al., 2001, Nielsen et al., 2006). Another type of vessel very susceptible to this phenomenon is fishing vessels. Due to regulatory limitations, their hull forms include hanging sterns and full midbodies in order to maximize both working space and storage capacity. The immersion of the stern as waves pass leads to large changes in waterplane area, which, in turn, causes the onset of parametric resonance in roll.

Few examples of accidents happened because of parametric roll were reported in literature. The most notorious is definitely the accident occurred to the *APL China* post-Panamax container ship, which suffered cargo losses for more than 50 million dollars (France et al., 2001). The PCTC *Aida* experienced two episodes of violent roll motions, hitting roll angles larger than 50 degrees (IMO, 2007). Parametric rolling may also have been the cause of severe material damage and injuries to passengers and crew of cruise ships *Grand Voyager* and *Pacific Sun* (MAIB, 2009).

By contrast, there is no evidence about parametric rolling involving fishing vessels. Probably this is due to the fact that these ships usually have small stability margins, thus a severe parametric roll episode could easily lead to capsizing and sinking, leaving no trace of the phenomenon. However, many studies demonstrated that fishing vessels are prone to develop parametric roll (de Juana Gamo et al., 2005), which implies a high risk for the ship and its crew.

One of the main characteristics of parametric roll is its very sudden onset. It develops in just few rolling cycles and there are few signs that can timely suggest the crew that the resonance is occurring. Therefore the exigency of a system that can predict the inception of a parametric rolling episode soon enough to give the crew time to take corrective actions and prevent heavy roll motions is clear.

The governing bodies (IMO, 2007), industry and the research community have full awareness of this fact. Warning systems based on polar diagrams (Amarcon Octopus[1], SeaWare enRoute[2]) have been the first response of the maritime industry to the call for decision support systems, which could help the master in counteracting the onset of parametric roll. These first generation warning systems are based on the combined analysis of weather forecast reports and ship sailing parameters, including heading and speed, in order to define resonance risk areas in a medium time horizon (15 to 30 minutes). These areas should be avoided by changing speed or altering course; however these counteractions could lead to delays or increase the fuel consumptions.

Although the currently commercialized decision support systems have been of great help to the master, at least by generating a general sense of awareness about the phenomenon, classification societies as Det Norske Veritas (Døhlie, 2006) have pointed out the need for second generation warning systems. The main feature of these novel systems should be the capability to predict/detect the onset of parametric roll in a short time horizon (few minutes) just shortly before it develops, allowing the crew to take immediate corrective actions.

In response to this need some research tanks have pursued different lines of research aiming at obtaining a real-time detection system, which analyzes the ship's motions and detects the possible occurrence of parametric resonance. Thus, preventive actions would be taken only when parametric roll is certainly developing, avoiding the potential drawbacks derived from taking unnecessary countermeasures. Model based approaches have been proposed by Holden et al. (2007) and McCue and Bulian (2007), whereas a signal based approach is at the core of the methods in Galeazzi et al. (2009a-b).

Holden et al. (2007) proposed an observer-based predictor, which estimates the eigenvalues of a linear second order oscillatory system. The predictor issues an alarm when the eigenvalues move into the instability region. The method showed good potential, but it was designed to only cope with regular wave excitation. McCue and Bulian (2007) exploited finite time Lyapunov exponents to detect the occurrence of parametric roll in irregular sea, but this method was not found to be sufficiently robust when tested against experimental data. Galeazzi et al. (2009a-b) proposed two complementary detection methods, which work in the frequency and time domain. The frequency domain method estimates the spectral correlation between the first harmonic of heave/pitch and the second harmonic of roll, whereas the time domain method is based on the generalized likelihood ratio test (GLRT) for non-Gaussian distributed signals, and it performs the hypothesis testing on a signal, which carries information about the phase synchronization between roll and heave/pitch. Those methods have been merged within a monitoring system for the early detection of parametric roll, and the vast testing done on experimental and full scale data of container ships in transit assessed the good capabilities to timely detect the onset of parametric roll, and the robustness against false alarms due to e.g. synchronous roll (Galeazzi et al., 2010).

In the present work, a different approach is proposed which relies on the use of artificial neural networks (ANNs) in order to forecast ship's motions in parametric roll conditions. ANNs are powerful mathematical tools capable of efficiently approximating any function, including nonlinear ones, by selecting the adequate number of layers and neurons (Cybenko, 1989). This property has been broadly exploited for time series forecasting in different fields, included physics, engineering or economics (Zhang et al., 1998). ANNs have been successfully applied also in the field of marine engineering for ship maneuvering and motion analysis (Ebada an Abdel-Maksoud, 2006, Xing and McCue, 2009).

In (Míguez González et al., 2010), the authors applied this tool for the prediction of parametric roll resonance in longitudinal regular waves. In particular multilayer perceptron neural networks (MPNNs) were used to forecast ship roll motion and acceleration with a prediction horizon ranging from 5 to 10 seconds. The MPNN showed good capabilities in predicting the behavior of roll as parametric roll resonance. Nevertheless the authors acknowledged the need of further investigating the efficacy of the proposed method in predicting the development of parametric roll in more realistic sailing conditions.

This work presents a step in that direction: the predictive capability of MPNN is tested against parametric roll developed in irregular seas. Different network set-ups are considered by increasing the number of neurons per layer, or by increasing the number of hidden layers. The MPNNs are validated against a high-fidelity nonlinear model of a fishing vessel (Neves and Rodríguez, 2006), where heave, pitch, and roll are fully coupled. The testing confirmed the good potential of using neural network for the prediction of parametric roll; in particular the MPNN provided reliable predictions up to 20 seconds ahead in some of the study cases.

ANN-BASED PREDICTOR FOR PARAMETRIC ROLL

Artificial Neural Networks

In this section we revisit some of the main aspects of artificial neural networks, providing the mathematical formalism about their working principles. The overview is based on (Haykin, 1999).

An ANN is a parallel distributed computational tool constituted by information-processing units called neurons, which has the capability of accumulating experiential knowledge to be used when needed. It is similar to the brain in two aspects:

- The acquisition of knowledge from the surroundings relies on a learning process
- The strength of the interneuron links, called synaptic weights, are employed to accumulate the gathered knowledge

The learning process is based on a learning algorithm, whose function is to change the synaptic weights to achieve a desired goal.

Each neuron performs the following operations: first each input is weighted by a synaptic weight w_{kj}, then all weighted inputs are added, and finally a bias b_k is added. This summation is then processed by an activation function, which limits the amplitude of the neuron output. Mathematically the neuron activity can be described as follows:

$$v_k = \sum_{j=1}^{m} w_{kj} x_j + b_k \tag{1}$$

$$y_k = f\left(v_k\right) \tag{2}$$

Where $x_1, x_2, \ldots, x_m$ are the input signals, $w_{k1}, w_{k2}, \ldots, w_{km}$ are the synaptic weights, b_k is the bias, v_k is the activation potential, $f(\cdot)$ is the activation function, and y_k is the neuron output.

The activation function should be selected depending on the analyzed data and the kind of problem to be solved. Three basic types of activation functions are: the Heaviside function (or threshold function); the piecewise linear function; the sigmoid function.

[1] www.amarcon.com
[2] www.amiwx.com

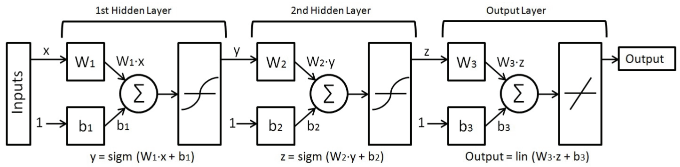

Fig. 1: Multilayer Perceptron Neural Network Architecture.

The complexity of the problems that the network can deal with depends on the number of hidden layers and neurons in each layer. This capacity increases with the number of neurons and layers, but only up to a limit. For a given function, no further improvements can be obtained by increasing the number of neurons and layers once the threshold is hit.

In this paper the authors employed an ANN with multilayer perceptron architecture (MPNN) whose structure is shown in Fig. 1. MPNNs are feedforward networks also called backpropagation networks because of the algorithm used for updating the weights and biases is called error backpropagation algorithm. This algorithm consists of two phases: the forward pass and the backward pass. In the forward pass a certain pattern is inputted to the network, which generates a chain of effects that propagate throughout the network layer by layer up to the output layer where the actual network response is produced. During this phase the synaptic weights are kept fixed. In the backward pass instead the synaptic weights are changed accordingly with a cost function, which determines how close the network response is to the real output. The error signal is propagated backward through the network, and the weights are adjusted such that the response of the network gets statistically closer to the desired response. Mathematically this is described as follows:

Consider a network with $N+1$ layers of neurons, and N layers of synaptic weights. The input and bias vectors of each layer are given by

$$\mathbf{x}^l = \left[x_1,\ldots,x_{m_l}\right]^T \in \mathcal{R}^{m_l}, \qquad 0 \le l \le N \tag{3}$$

$$\mathbf{b}^l = \left[b_1^l,\ldots,b_{m_l}^l\right]^T \in \mathcal{R}^{m_l} \tag{4}$$

and the matrix of synaptic weights is

$$\mathbf{W}^l = \begin{bmatrix} w_{11}^l & w_{12}^l & \cdots & w_{1m_{l-1}}^l \\ w_{21}^l & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ w_{m_l1}^l & \cdots & \cdots & w_{m_lm_{l-1}}^l \end{bmatrix}, \quad \mathbf{W}^l \in \mathcal{R}^{m_l} \times \mathcal{R}^{m_{l-1}} \tag{5}$$

Forward pass: the input vector $\mathbf{x}^0$ is converted into the output vector $\mathbf{x}^N$ by calculating

$$\mathbf{x}^l = f\left(\mathbf{v}^l\right) = f\left(\mathbf{W}^l\mathbf{x}^{l-1} + \mathbf{b}^l\right), \qquad 0 \le l \le N \tag{6}$$

where $\mathbf{v}^l$ is the vector of activation potentials.

Output local gradient: the output local gradient vector δ^N is computed as function of the error between the desired output $\mathbf{y}^d$ and the actual output $\mathbf{x}^N$

$$\delta^N = f'\left(\mathbf{v}^N\right)\left(\mathbf{y}^d - \mathbf{x}^N\right) \tag{7}$$

Backward pass: the error signal is backpropagated through the network by computing the hidden layer local gradient vectors

$$\delta^{l-1} = f'\left(\mathbf{v}^{l-1}\right)\left(\mathbf{W}^l\right)^T \delta^l, \qquad N \ge l \ge 1 \tag{8}$$

Weights update: the synaptic weights and biases are updated according to the following relations

$$\Delta\mathbf{W}^l = \eta\delta^l\left(\mathbf{x}^l\right)^T \tag{9}$$

$$\Delta\mathbf{b}^l = \eta\delta^l \tag{10}$$

where η is the learning rate parameter.

It is possible to prove that Eqs. 9-10 are found as gradient descent on the performance index

$$E = \frac{1}{2}\mathbf{e}^T\mathbf{e} \tag{11}$$

where $\mathbf{e} = \mathbf{y}^d - \mathbf{x}^N$ is the network output error (Haykin, 1999).

Parametric Roll Prediction System

The main neural network architecture utilized in this work is a multilayer perceptron network with two hidden layers, 40 neurons per layer, and one output layer. This initial structure is modified by e.g. increasing the number of neurons per layer, or the number of layers, in order to compare the prediction performance of different architectures.

The network is fed with time series of roll motion, which are 20 seconds long and sampled at a frequency F_s = 2Hz; hence the input vector $\mathbf{x}^0$ has 40 components. The network has only one output, which is the one step-ahead prediction. By substituting part of the input vector with the network output values, and recursively executing the system, longer predictions can be obtained from the initial 20 seconds. However, as the number of iterations grows, the prediction performance deteriorates accordingly.

The length of the roll time series has been selected taking into account two factors. On one hand the natural roll period of the vessel chosen for the testing is about 7.5 seconds. On the other hand parametric rolling fully develops in a short period of time, usually no more than four rolling cycles (IMO, 2004). Therefore if the network prediction should be used e.g. together with a diagnostic system for the timely detection of parametric roll inception the time lapse that must be analyzed should be shorter than four roll periods.

As activation functions in the hidden layers, tan-sigmoid functions have been selected (y = tanh x). These functions have proved to be more adequate for dealing with highly non linear systems than, for example, step or linear ones (Demuth et al., 2009), and they are the most commonly used in the multilayer perceptron architecture. A linear function ($y = x$) was instead selected in the output layer.

The performance of the neural network can be improved by normalizing the input and target data prior to being processed. During the training phase inputs and target values are normalized such that they fall in the range [-1,1], obtaining two scaling factors n_1 and n_2 respectively. Once trained, these factors are used for normalizing test inputs and de-normalizing their corresponding outputs.

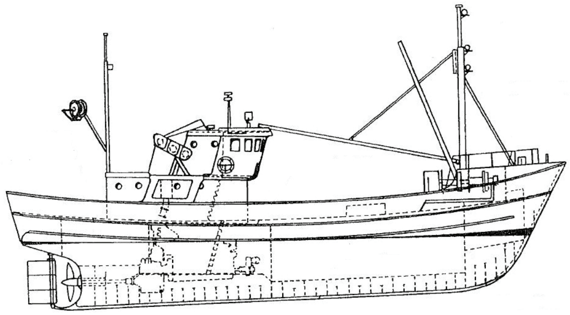

Fig. 2: Test vessel profile view.

As shown, the training algorithm is responsible of modifying the weights and biases in order to reduce the error between the network's prediction and the target value. In this work, the authors have chosen the Levenberg-Marquardt (L-M) algorithm (Demuth et al., 2009), instead of using basic gradient descent.

L-M is a training method optimized for solving problems of function approximation. Based on the Gauss-Newton method, it overcomes the difficulties of computing the hessian matrix **H** of the performance index hessian by approximating it using the Jacobian matrix **J** ($\mathbf{H} = \mathbf{J}^T\mathbf{J}$). In this case, the weights update is

$$\Delta\mathbf{W}^l = \left[J^T J + \mu I\right]^{-1} J^T \cdot e \cdot \left(\mathbf{x}^l\right)^T \qquad (12)$$

$$\Delta\mathbf{b}^l = \left[J^T J + \mu I\right]^{-1} J^T \cdot e \qquad (13)$$

where μ is a variable parameter called damping factor. When this parameter is large, the L-M is equivalent to gradient descent; when it is small, it becomes the Newton method. For measuring the aforementioned error, the mean squared error (MSE) was chosen as performance function.

RESULTS

Fishing Vessel Model

Among the ship classes being susceptible to parametric roll, fishing vessels have the smallest stability level; therefore their capacity to withstand a parametric roll event is the smallest as well. In this case the high amplitude rolling motions could easily lead to capsizing, with the inherent high risk for the crew's life.

Taking into account that fishing vessels are those for which a parametric rolling warning system could be extremely necessary from a safety point of view, the authors decided to test the performance of the proposed method on this type of ship. However it is worth mentioning that the proposed prediction system is independent of the vessel it is applied to (it only depends on the motion time series used for the training process); hence the methodology shown in this work could be easily applied to any other type of vessel.

The ship chosen for this work is a midsized trawler, that has been broadly studied (Neves et al., 2002), and that has a large tendency to develop parametric roll resonance already in relatively low sea states. Table 1 presents the main characteristics of the trawler; while Figs. 2-3 show the profile view and the hull forms. The operational parameters - i.e. forward speed, displacement and weight distribution - have been kept constant for all test cases.

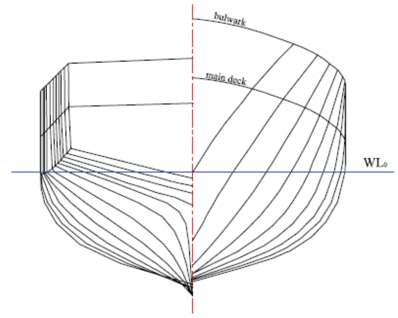

Fig. 3: Test vessel hull forms.

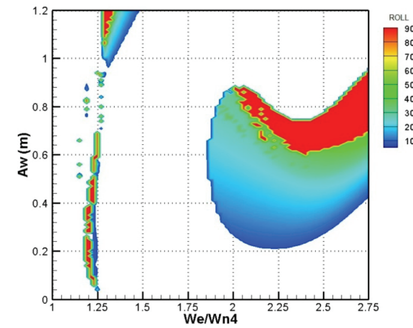

Fig. 4: Areas of instability for the test vessel.

Parametric rolling is more likely to occur when the wave encounter frequency is approximately twice the ship roll natural frequency, and when the wave amplitude is within a ship dependent range. Figure 4 shows the ship roll angle due to parametric rolling as a function of wave amplitude and of the ratio between the encounter frequency and the natural roll frequency, for the case of regular waves, head seas (Neves et al., 2006). As it can be seen, large roll angles develop not only when the frequency ratio is exactly equal to 2, but also between 2 and 2.75, for wave amplitudes ranging from 0.2 m to 0.8 m. Simulations were run by tuning the wave parameters such that the roll dynamics falls within the large region of instability shown in Fig. 4.

Table 1: Test vessel main characteristics.

Overall Length	25.91 m
Length between Perpendiculars	22.09 m
Breadth	6.68 m
Depth	3.35 m
Draft	2.48 m
Displacement	170.3 t
Long. Radius of Gyration	5.52 m
Metacentric Height	0.37 m
Froude Number	0.3

Ship motions have been simulated by exploiting the mathematical model developed by Neves and Rodríguez (2006). This is a three-degrees-of-freedom nonlinear model, where heave, pitch and roll motions are obtained in a coupled way, taking in consideration the influence of "longitudinal plane" motions (heave and pitch) on the appearance of parametric roll resonance. This model has proved to accurately compute ship roll responses in resonant conditions, for the case of regular waves and head seas. Further details about this model can be found in (Neves and Rodríguez, 2006).

Regular Waves with Time-varying Amplitude

As first attempt to approximate a realistic seaway scenario, which can induce the onset of parametric roll the following test case has been designed. The ship model was excited by a regular wave with time-varying amplitude ranging between 0.2 m and 0.5 m, and constant wave frequency equal to 1.26 rad/s, which corresponds to an encounter frequency of 1.98 rad/s (frequency ratio equal to 2.3). This gave rise to ship responses in roll where parametric resonance is always present, but with variable roll amplitude. The resulting roll time series can be seen in Fig. 5. The corresponding wave amplitude in each time interval of the simulation is reported in Table 2.

The reason behind this approach was to evaluate the performance of the MPNN while dealing with a roll dynamics that does not reach a steady state response (typical of parametric rolling event in regular seas with constant wave amplitude and frequency), but that alternates growing and decaying oscillations in response to changes in the wave amplitude, similarly to what happens in a real seaway.

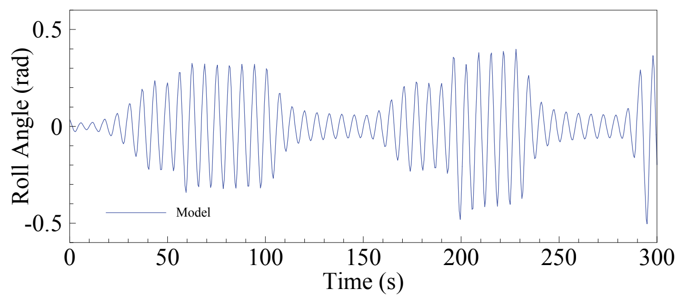

Fig. 5: Roll motion test time series in regular waves.

Table 2: Time intervals and corresponding wave amplitude

Time (s)	Wave Amplitude (m)
0 - 50	0.3
50 - 100	0.4
100 -150	0.2
150 - 190	0.3
190 - 230	0.5
230 - 280	0.2
280 - 300	0.5

The training cases were generated using the same mathematical model employed for the test time series. In order to feed the network with all possible representative cases, it has been necessary to use time series where resonance was fully developed and also time series without resonant behavior, equivalent to a roll decay condition. The former provides data for the case where roll amplitude increases, while the latter provides data for the cases where roll motion reduces, that is, transient behavior from a resonant to a non resonant roll motion. Taking into account that this transient depends on the initial roll amplitude (roll amplitude during the parametric roll event), several initial conditions were used for the generation of the training cases; this

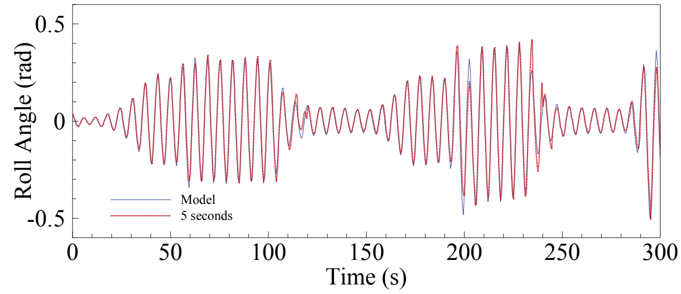

Fig. 6: Regular waves: 5 seconds forecast.

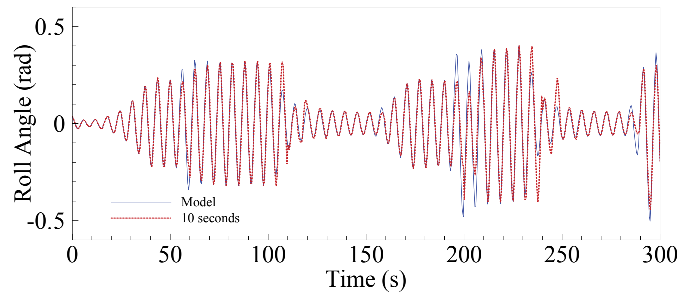

Fig. 7: Regular waves: 10 seconds forecast.

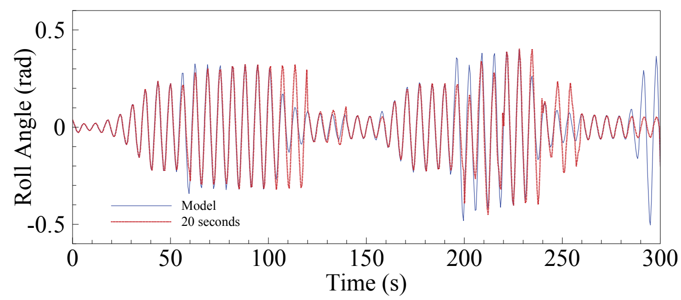

Fig. 8: Regular waves: 20 seconds forecast.

was done in order to feed the network with the largest possible amount of information about the ship's roll motion.

A training data set of 66 time series was generated, with wave amplitudes ranging from 0.1 m to 0.6 m in steps of 0.05 m, wave frequency equal to 1.26 rad/s, initial roll angles ranging from 5 degrees to 30 degrees, in steps of 5 degrees, and duration of 50 seconds. Once computed, these time series were divided in sets of 40 + 1 values, which are equivalent to the 40 inputs of the network and their corresponding output. Each one of these data sets is a training case for the system. Hence, a total number of 4026 training cases was obtained.

Considering that the initialization of the training phase is a random process - the first set of weights and biases are randomly generated - the same set of training cases can generate different results for successive initializations. Consequently the performance of the network will also differ from training to training. Therefore the training process has been repeated 50 times, and the best network structure out of the 50 cases was selected based upon the network performance index.

In order to obtain forecasts longer than one step ahead (0.5 seconds), the system has been recursively executed in order to obtain 5, 10 and 20 seconds long predictions. The obtained results for the three different prediction horizons, and their corresponding errors, are illustrated in Table 3 and Figs 6-8.

Table 3: Prediction performance: mean squared error.

Forecast Horizon	MSE
5 seconds	0.00069
10 seconds	0.00180
20 seconds	0.00530

The prediction made with 5 seconds horizon (Fig. 6) accurately tracks the test time series. Analyzing the forecast, the parametric rolling events that develop around the second 25, 150 and 280 can be predicted. Results of the 10 seconds prediction (Fig. 7) are also quite good. However, around $t = 250$s, the network slightly over predicts the roll amplitude, but just after one roll period the prediction is again well tracking the ship's roll motion. In the last case the prediction horizon is 20 seconds (Fig. 8) and it can be observed that the general behavior is still rather good, but there exists three main areas around 120s, 250s and 280s where the network fails. The last case is particularly interesting as the network prediction clearly underestimates the ship's roll oscillation.

Irregular Waves

Aiming at analyzing the performance of neural networks as predictors of ship's behavior in realistic sailing conditions, another simulation scenario was set up. While maintaining the head seas hypothesis, the trawler model was excited by irregular waves.

The wave motion is modeled applying the linear long crested model, where wave elevation as a function of time is computed as

$$\eta(t) = \sum_{k=1}^{N} A_k \cos\left[\omega_k t + \varepsilon_k\right] \tag{14}$$

In Eq. (14) ε_k represent the uniformly distributed random phase, ω_k is the wave frequency selected for the spectrum computation, and A_k is the random wave amplitude, which follows a Rayleigh distribution with a mean squared value of

$$E\left[A_k^2\right] = 2S(\omega_k)\Delta\omega_k \tag{15}$$

where $S(\omega_k)$ is the selected wave spectrum and $\Delta\omega_k$ is the frequency resolution.

Note that some of the model coefficients were not recomputed for the irregular wave case; hence quantitative roll motion values will not be relevant, but the roll motion time series can be used for a qualitative analysis.

Considering the random nature of wave excitation in this simulation scenario, both training and test cases have been generated with the same wave conditions. A Jonswap spectrum has been selected, with a peak shape parameter of 5, σ_a and σ_b values of 0.05 and 0.07 and 500 frequency values for its computation, ranging from 0.2 rad/s to 5 rad/s. The peak period T_p was set to 3.2 seconds, coinciding with the encounter period used in the regular wave test case (encounter peak frequency of 1.98 rad/s, frequency ratio equal to 2.3) and the significant wave height was set to 1.2 m, in order to define wave conditions where parametric rolling is likely to occur.

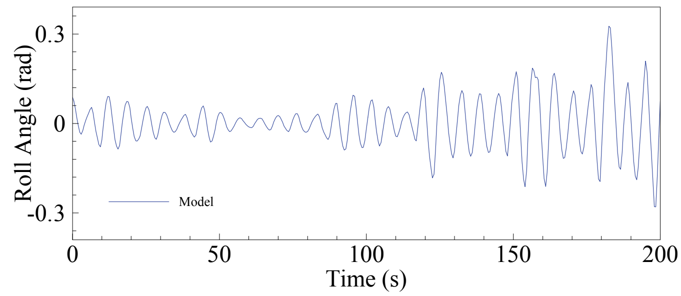

Fig. 9: Irregular waves: first test series.

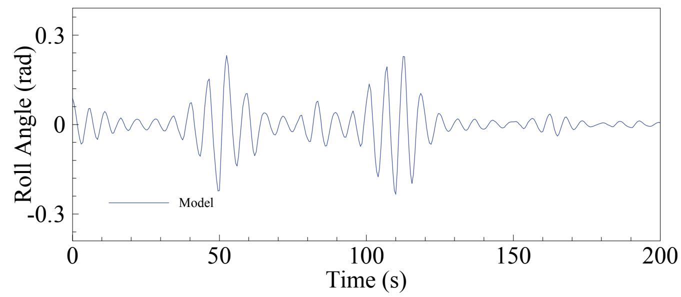

Fig. 10: Irregular waves: second test series.

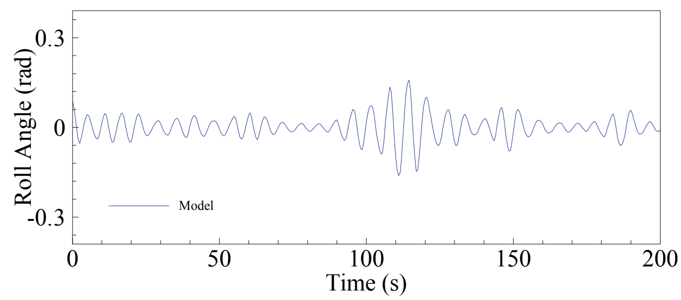

Fig. 11: Irregular waves: third test series.

The training data set is composed of 50 time series, each 200 seconds long. As in the regular wave scenario, the time series are split in groups of 40 inputs and 1 output, which correspond to a total number of 18050 training cases. Another three time series (see Figs. 9-11) were generated to be used as test cases.

In this scenario three different MPNN architectures were tested in a comparative study to assess which configuration provides the best roll motion prediction. First, a two hidden layer MPNN with 40 neurons per layer has been set up and trained. By feeding the resulting structure with the three test cases, and recursively executing it for 20 times, the 10 seconds ahead predictions were obtained.

The initial network structure was changed by increasing the number of neurons in the hidden layers up to 45. This, in turn, should also increase the network prediction accuracy, but only up to a certain limit. The third tested network has instead an increased number of hidden layers. To avoid that a deeper network entails a longer training time due to the larger number of network parameters (weights and biases) to be estimated, the increase in the number of layers was accompanied with a reduction in the number of neurons per layer. This generates a network with the same amount of parameters as the former two, but with a different structure and, hence with a different behavior. The proposed network has then three hidden layers and 30 neurons per layer.

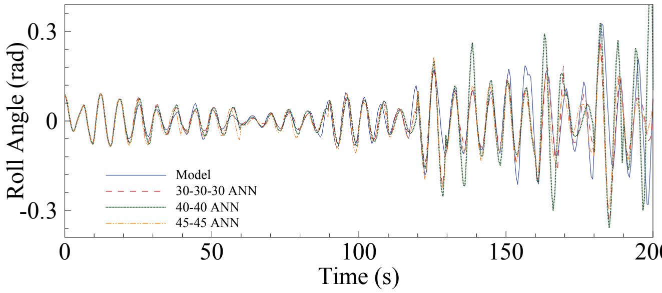

Fig. 12: Irregular waves: first test case.

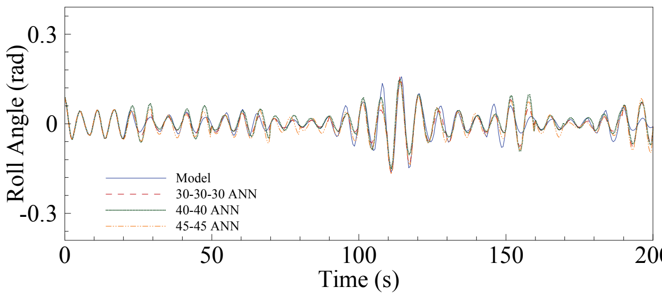

Fig. 14: Irregular waves: third test case.

After training the two new structures, the 10 seconds ahead forecasts for the three test cases were computed. The obtained predictions with the three different structures and their corresponding prediction errors are shown in Figs. 12-14 and Table 4. From the figures and the MSE values, it can be clearly seen that the best performing structure is that with three hidden layers, although it has a smaller number of neurons. Between the other two, the expected results were obtained, as the 45 neuron performs better or equal to that of 40 neurons. However, the difference in performance between these structures is much smaller than that between the two and the three hidden layers networks.

The predictions provided by the three layers network are very accurate in all test cases, precisely tracking the ship roll response. However, taking into account that the ship model was not validated for the irregular wave scenario, a new testing campaign should be conducted possibly including model tank tests in irregular seas, in order to definitely assess the capability of neural networks to accurately forecast ship roll motion as parametric roll in realistic seaway conditions.

DISCUSSION

Two aspects are crucial for the proposed roll motion forecasting system: the time horizon in which reliable predictions are made, and the high accuracy of these predictions. Two scenarios are feasible: the prediction system is directly used by the fisherman/captain in the wheel house to monitor the ship's behavior and eventually alert the rest of crew busy in the fishing activities; the prediction system provides roll motion forecasts to a diagnostic system used for automatic detection of parametric roll.

In the first situation, to have a sufficiently long prediction horizon is a condition sine qua non the crew cannot take countermeasures to guarantee their safety and bring the vessel out of the risky zone. It is also essential to have accurate predictions because the captain would not like to put in alert his crew if there is no need for that; a false alarm could determine e.g. the loss of catch, or crew's member injuries due to the spread of panic, or even the execution of rough maneuvers, which may really lead the vessel into unstable motions.

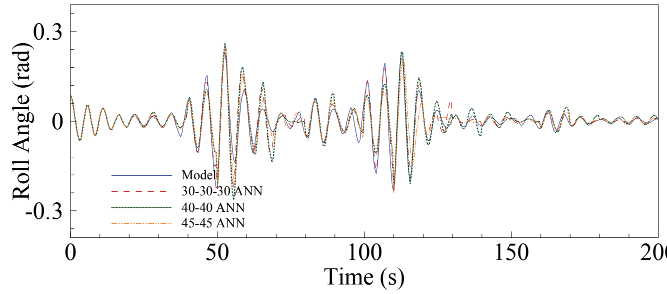

Fig. 13: Irregular waves: second test case.

Table 4: Prediction performance: mean squared error.

Test Case Number	2 layers 40 neurons	2 layers 45 neurons	3 layers 30 neurons
1	0.00890	0.00320	0.00280
2	0.00085	0.00089	0.00058
3	0.00052	0.00050	0.00035

In the second scenario the two aspects are as important as in the first. The time span of the forecasting is an issue even if it is a detection system processing the predictions simply because it will still be the captain who will have to promptly respond to an issued alarm. In fact current regulations prohibit to any system to directly inject control signals into the autopilot, in case one was available onboard. The accuracy of the predictions is substantial because, although it is not possible to infer a priori that a poor prediction will determine poor detection performances, it is sensible to think that a highly accurate forecast may require a less robust diagnostic system.

Considering the prediction performance showed by the MPNN in the analyzed sailing conditions, and by taking in account the small size and inertias of the test vessel, the authors think that a combined predictor could be employed, using a (20 - 10) prediction scheme. The 20 seconds forecast would be used to display preventive alarms, which could be used to alert the crew about possible large roll oscillations; whereas the 10 seconds accurate predictions would be used to confirm or reject the alert situation. A time span of 10 seconds could also be enough for the master to change ship's speed or course.

CONCLUSIONS

This work presented an application of ANNs for forecasting the roll motion of a fishing vessel in parametric resonance condition. The main objective of the described method is to accurately forecast the ship's roll motion within a time span of few seconds, generally between 10 and 20. The forecasting system consists of a multilayer perceptron neural network. Different network architectures with different width (number of neurons) and depth (number of layers) have been tested.

The vessel used for testing is the well known transom stern fishing vessel, which showed a high tendency of developing parametric resonance. The ship's motions were obtained using a three-degrees-of-freedom nonlinear model, where heave, pitch and roll are fully coupled.

Two different scenarios were taken into account to evaluate the ability of this kind of systems to accurately forecast the ship's roll motion in a realistic seaway. The first consisted in a regular wave case with time varying amplitude. In this case, the network was used to make predictions of 5, 10 and 20 seconds in advance, from a input vector of 20 seconds. The obtained results were very accurate, especially in the 5 and 10 seconds case, presenting a slightly worse performance in the 20 seconds ahead prediction. The second scenario consisted in an irregular wave case, were waves were generated according to the Jonswap spectrum, with peak values set to lead to a parametric rolling behavior. Due to the higher complexity of this case, a comparison between three different network configurations has been done, in order to improve the performance of the network set-up tested in the regular wave case.

Three test cases have been considered, using the MPNN for making 10 seconds ahead predictions of roll motion. These tests showed very promising results, especially for the three hidden layers network, which precisely forecasted the simulated roll motion. The obtained results strengthen the idea of exploiting neural network to accurately predict highly nonlinear ship dynamics, as roll in parametric resonance, in realistic seaway conditions.

Accurate predictions with a time horizon of 10 seconds have been obtained; this time could be enough to allow the captain to alert the crew and take counter measures to bring the vessel out of the dangerous area. However, further investigations are needed to extend the prediction horizons. At the same time, the need of model tank testing to verify the overall performance of the system in a highly realistic scenario is clearly acknowledged.

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