An Artificial Neural Network Approach for Parametric Rolling Prediction

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Abstract

Parametric rolling is a major issue affecting nowadays modern fishing and containership fleets. This sudden phenomenon implies huge rolling oscillations that can cause cargo damage, crew injuries and may lead to the loss of the vessel in the most severe cases. Due to its short development time and the nonlinear behaviour of parametric rolling, a real time detection system could not be fast enough to generate a response able to take the ship out of the risk area. Thus, a prediction system appears to be an adequate tool to provide information in advance, allowing the crew or a control system to take corrective actions.

The present work describes the ongoing activity in a research project we are working on for the development of a parametric rolling prediction and detection system. This system is based on artificial neural networks and on their well known capabilities for predicting nonlinear system behaviour. In this case, ship motions are simulated using the three degree of freedom nonlinear coupled model developed by Neves and Rodríguez (2006), which has been proven to accurately reproduce parametric rolling. The ship used for this analysis is a transom stern fishing vessel having an identified tendency to develop parametric rolling. The Neural Networks used here take roll angle as system inputs producing a forecast of rolling angle as output. These networks are trained by using Neves and Rodríguez (2006) model as simulator in different longitudinal wave conditions leading to parametric rolling. Finally, the trained networks are used to predict ship behaviour for different time windows in advance, obtaining very promising results for making short term predictions that can allow crews to take actions and prevent the appearance of parametric rolling or even to activate an automatic system which takes these actions by itself.

Keywords

Parametric; roll; neural; networks; ship; stability

Introduction

Parametric rolling is a well known phenomenon which implies the sudden appearance of very strong roll motions, that could easily lead to severe cargo, structural and crew damage and in the worst cases, to the loss of the vessel. It is more frequent in head or stern seas, when the wavelength is near the length of the vessel and the encounter frequency doubles the ship´s natural roll frequency and over an amplitude threshold. It is produced by the waterplane area variations due to wave passing and pitch and heave motions, which imply periodic changes in transverse restoring arms. Vessels with pronounced bow flares and overhanging sterns are those more affected by this phenomenon, such as containerships, cruise vessels and also fishing vessels [Shin *et ál.* (2004)]. Parametric rolling happens in a very short period of time and also due to the huge inertias of most of these ships, it is impossible for the crew to take effective corrective actions once it has started. Thus, a system that can predict in real time the development of parametric rolling well in advance, at least long enough in advance so as to allow the crew to take actions, or even joined with a parametric rolling prevention control system that takes these actions by itself, could be a great help to avoid the previously described problems.

The IMO guidelines to avoid dangerous situations in adverse weather [IMO (2007)] and some on-line software try to help the crew to prevent resonance by defining potentially dangerous conditions where resonance is likely to occur. Due to this fact, increased fuel consumptions or delays can be produced while taking alternative routes or reducing speed, but without the complete certainty that resonance is going to happen. This is the reason why, in recent years, several lines of research have been aiming to obtain a detection system in real time to analyze the instantaneous operation of the ship (through the analysis of its motion) and to detect the possible appearance of resonance time before it occurs. Thus, preventive actions would only be taken if parametric rolling is really developing, avoiding the potential drawbacks that could lead to measures that ultimately were not needed.

To date, there are few published studies about this matter. Holden *et ál.* (2007) propose a system based on a second order oscillator modelling the rolling motion of the vessel. McCue and Bullian (2007) propose a system based on the analysis of the Lyapunov exponents associated to a mathematical roll model of the vessel, conducting a series of experiments under irregular waves. Lately, Galleazzi *et ál.* (2009) developed a prediction system based on the analysis of the energy flow between heave and pitch first harmonics (directly excited by wave motions) and the second harmonic of roll.

In this work, another approach for parametric rolling detection is presented. The use of neural networks represents a new alternative to address the problem, based on the ability that the artificial neural networks have to simulate the behaviour of nonlinear functions [Cybenko (1989)]. Neural networks are biological–like systems which learn by themselves a given behaviour from a series of examples, called training cases. After training, neural networks are capable of dealing with data different from that used for training. Their accuracy depends on the similarity between these new data and those used for training and the structure of the network. The successful applications of neural networks in other fields related to ship stability include anti-rolling control systems (tanks, fin stabilizers, rudder roll stabilization) and auto pilots [Jones *et ál.* (2003), Li *et ál.* (2005), Alarcin and Gulez (2007)]. In the case presented here, a multilayer perceptron neural network is used for the prediction of a roll motion time series, generated using the three degree of freedom coupled nonlinear model of a transom stern fishing vessel developed by Neves and Rodríguez (2006). The training cases are generated the same way. Different situations are simulated in order to generate training and test cases, including the range of frequencies and amplitudes where parametric rolling occurs for the aforementioned fishing vessel. This forecasting system can be used to predict ship motion in a variable time window, depending on the precision needed, and which may be analyzed to evaluate the development of parametric rolling.

Numerical Model

Numerical Model

In the present work, ship motions are modelled using the three degree of freedom model developed by Neves and Rodríguez (2006). This non-linear model describes ship roll, pitch and heave motions in a coupled way using third order Taylor series expansions and is able to reproduce parametric rolling in a very accurate way. The ship used here is a transom stern fishing vessel, with a high tendency to develop parametric rolling. To describe ship motions in these three degrees of freedom, two orthornormal reference systems are stated, one fixed at the mean ship motion (ship speed) and another fixed to the ship, with its XY plane coinciding with the sea surface in the absence of excitations or disturbances, and with the OZ axis pointing upwards and containing the centre of gravity. The ship equations of motion, considering three degrees of freedom, can be written this way:

$$(\tilde{M}+\tilde{A})\cdot\ddot{\vec{s}}+\tilde{B}(\dot{\phi})\cdot\dot{\vec{s}}+\vec{C}_{res}(\vec{s},\zeta)=\vec{C}_{ext}(\zeta,\dot{\zeta},\ddot{\zeta}) \qquad (1)$$

Where $\vec{s}(t)=\left[z(t)\;\;\phi(t)\;\;\theta(t)\right]^T$ is the position vector (including heave translation and roll and pitch angles), $\tilde{M}$ is the system mass matrix, $\tilde{A}$ represents the hydrodynamic added mass matrix, and $\tilde{B}(\dot{\phi})$ represents the damping matrix. $\vec{C}_{res}(\vec{s},\zeta)$ is the vector of non-linear restoring actions, dependent on the relative motions between ship hull and wave elevation $\zeta(t)$; The vector $\vec{C}_{ext}(\zeta,\dot{\zeta},\ddot{\zeta})$ represents the external excitation forces, including Froude – Krylov and diffraction forces, dependent on wave direction, encounter frequency ω_e, amplitude A_w and time [Neves and Rodríguez (2006)]:

$$\vec{C}_{ext}(\zeta,\dot{\zeta},\ddot{\zeta})=\vec{C}_{ext(FK)}(\zeta)+\vec{C}_{ext(Diff.)}(\dot{\zeta},\ddot{\zeta}) \qquad (2)$$

In this model, all terms in matrices $\tilde{A}$ and $\tilde{B}$ are calculated using potential theory, except roll damping $K_{\dot{\phi}}(\dot{\phi})$, where non-linear contributions to the second order must be included:

$$K_{\dot{\phi}}(\dot{\phi})\dot{\phi}=K_{\dot{\phi}}\dot{\phi}+K_{\dot{\phi}\cdot|\dot{\phi}|}\dot{\phi}\left|\dot{\phi}\right| \qquad (3)$$

Actions due to ship motions in still water and wave effects along the hull may be expressed up to third order using Taylor series expansions and defining a generalized vector $\vec{q}=\left[\vec{s},\zeta\right]^T$ such that:

$$\begin{aligned}\vec{C}_{Pos}&=\sum_{i=1}^{4}\left.\frac{\partial\vec{C}_{Pos}}{\partial q_i}\right|_0 q_i+\frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4}\left.\frac{\partial^2\vec{C}_{Pos}}{\partial q_i\partial q_j}\right|_0 q_iq_j\\&+\frac{1}{6}\sum_{i=1}^{4}\sum_{j=1}^{4}\sum_{k=1}^{4}\left.\frac{\partial^3\vec{C}_{Pos}}{\partial q_i\partial q_j\partial q_k}\right|_0 q_iq_jq_k\end{aligned} \qquad (4)$$

In this case, linear Airy Theory is used for modelling wave elevation. Taking also into account that we´re considering head seas case (and thus longitudinal waves), the equation of wave elevation is:

$$\zeta(x,t) = A_w \cdot \cos\left[k \cdot x + \omega_e \cdot t\right] \tag{5}$$

The terms of equation (4) that are not dependent on $\vec{s}(t) = \left[z(t) \;\; \phi(t) \;\; \theta(t)\right]^T$, represent linear and non-linear Froude-Krylov forces and can be expressed as follows:

$$\vec{C}_{ext(FK)}(\zeta) = \left.\frac{\partial \vec{C}_{Pos}}{\partial \zeta}\right|_0 \cdot \zeta + \frac{1}{2} \left.\frac{\partial^2 \vec{C}_{Pos}}{\partial \zeta^2}\right|_0 \cdot \zeta^2 + \frac{1}{6} \left.\frac{\partial^3 \vec{C}_{Pos}}{\partial \zeta^3}\right|_0 \zeta^3 \tag{6}$$

Taking this into account,

$$\vec{C}_{res} = \vec{C}_{pos}(z \;\; \phi \;\; \theta \;\; \zeta) - \vec{C}_{ext(FK)}(\zeta) \tag{7}$$

These equations present a nonlinear model where, unlike other approaches, roll motion is coupled to the other two degrees of freedom. All the details of the model and the derivation of all the coefficients can be found in Neves and Rodríguez (2006).

Test Vessel

The ship used for this work is a well studied fishing vessel with a transom stern that has a natural tendency to easily develop parametric rolling in not very heavy sea states [Neves and Rodríguez (2006)]. Its main characteristics, hull forms and data used in the experiments are included in the following table:

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
Metacentric Height	0.37 m
Froude Number	0.3

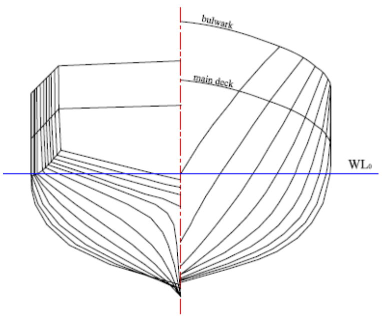


Fig. 1: Test vessel hull forms

The appearance or not of parametric rolling would depend on some parameters, taking in account that we´re under the head sea case (and so, ship heading – wave propagation direction angle χ is 180º). These parameters are encounter frequency $\omega_e = \omega - \frac{u \cdot \omega^2}{g} \cos \chi$, wave frequency ω and wave amplitude A_ω (considering other ship related parameters, such as ship roll natural frequency (ω_{n4}), ship speed (u), etc. to be constant). As mentioned above, parametric rolling appears when encounter frequency is about twice the natural roll frequency and when wave amplitude is over a minimum threshold. In the case of the ship under study, roll steady state angle is plotted as a function of wave amplitude and encounter frequency – natural roll frequency ratio. The large coloured area of Figure 2, where parametric rolling appears in this case, is where our study will be focused.

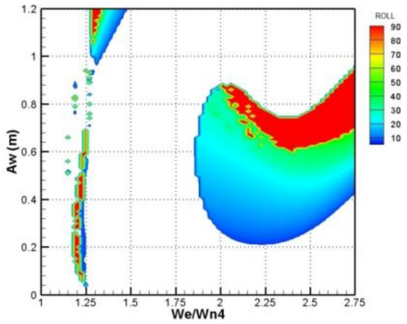


Fig. 2: Test vessel. Areas of stability

Neural Network Prediction System

Neural Networks

Neural networks are “biological inspired” systems formed by a series of interconnected neuron layers which are able to reproduce complex behaviours after a training process. In our case, the multilayer perceptron architecture was selected. These networks present the following structure:

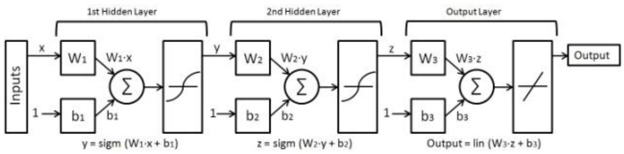


Fig. 3: Neural Network Architecture

Basically, in each neuron, the inputs are weighed, a bias is added and a summation of all the inputs is carried out. This summation is then processed by an activation function and the result is sent to the next neuron layer.

The training process consists in feeding the network with known data, including inputs and their corresponding outputs, and adjusting the weights and biases to minimize error between target and network result. In this kind of multilayer networks, the training algorithm being used here is the well known backpropagation algorithm. In this algorithm the error is propagated from the output layer to the preceding ones. Basically, in each iteration a performance function (for example the mean squared error) is computed. Then, the weights and biases are modified following the gradient of the performance function, and also taking in account a learning rate which defines the value of this modification. Gradient descent algorithms are the simplest of backpropagation algorithms, but there are more complex ones which increase convergence speed, and that can be based, among others, on heuristic techniques or numerical optimization techniques [Demuth *et ál.* (2009)]. Once the network is properly trained, it can obtain quite good results from unknown inputs, always depending on how good the training has been.

Activation functions should be selected depending on the analyzed data and the kind of function that needs to be forecasted. They may be sigmoid, threshold, linear and other kinds of functions. The number of layers and neurons in each one increases the capacity of the network to deal with more complicated functions. Even though it has been demonstrated that a single hidden layer network can follow any function with arbitrary precision, it is also true that in this case an infinite number of neurons may be required. Consequently, it is quite usual to employ networks with two or three layers.

Neural Network Prediction System

The selected architecture for the multilayer perceptron consists of two hidden layers of between 30 and 40 neurons, depending on the case under study, with 40 inputs and one output and tan-sigmoid activation functions. These forty inputs represent twenty seconds of the ship rolling motion time series (0.5 seconds of time step), while the output represents the next time step. The network can be used recursively, so a number of outputs equal to the number of iterations can be obtained from the initial set of 40 time steps. It is clear that increasing the number of iterations would also decrease the performance of the network. These twenty seconds have been selected taking into account the ship's natural rolling motion period, which in the case under study is about 7.5 seconds. Parametric rolling takes place in a short period of time, usually no more than four rolling cycles [IMO (2004)]; as the objective of this work was to detect the phenomenon some time before it develops, the time lapse that has to be analyzed should be shorter than those four rolling cycles. As activation functions, tan-sigmoid functions have been selected in the hidden layers, as we´re modelling a highly nonlinear system and data are both in the negative and the positive sides. In order to improve network efficiency, the data is normalized prior to its processing by the network and a linear function is used in the output layer to obtain data in the whole range of the time series amplitude.

In the case presented, training was carried out using the Levenberg-Marquardt algorithm with momentum, as its performance is usually good in function approximation problems [Demuth *et ál.* (2009)]. It uses the Jacobian matrix (including first derivatives of the network errors with respect to weights and biases) and a vector of errors of the network to update weights and biases. Momentum tries to avoid the probability of the system to be stopped by a local minimum in the error function. The mean squared error has been chosen as performance function.

Test Cases

The following tests were carried out in order to prove the capacity of the system to properly "forecast" future values of a ship motion time series that can be used for parametric rolling prediction. Taking in account that in the case under study the only parameters that influence the appearance of parametric rolling are wave frequency and amplitude (as ship operational conditions are assumed to be constant), three different studies were carried out, in order to evaluate the system behaviour under the variations of each one of those parameters. In the first one, wave amplitude is taken as constant as wave frequency is modified. In the second one, frequency is taken as constant while amplitude is modified. Finally, both parameters are taken as variable. The training cases are obtained from the results of the aforementioned mathematical model, generating a 200 second time series for every combination of wave frequency and amplitude. These time series are truncated when steady-state rolling is reached, in order to prevent the introduction of redundant data in the training process; these redundant values would give higher weights to these areas of the time series, reducing the performance of the prediction in the transient region.

The truncated time series are divided into groups of 40+1 time steps that would represent the 40 inputs and the output of the neural network. Each one of these groups will be a training case for the system. In the different test cases, the prediction network was recursively executed 5 and 10 times, in order to make predictions of 5 and 10 seconds in advance. After those 5 or 10 seconds, a new prediction is made based on another 20 seconds obtained from the model time series (simulating the effect of an onboard sensing system) and so on. This way we can generate a whole predicted time series of the same length as the original one. In some cases, the whole predicted time series is generated only from the first 20 seconds, by executing the network recursively until the complete length is generated. These predictions should be long enough to respectively give time to take automatic (5 seconds) or crew (10 seconds) preventive actions to avoid an imminent hypothetical parametric rolling episode that is being predicted.

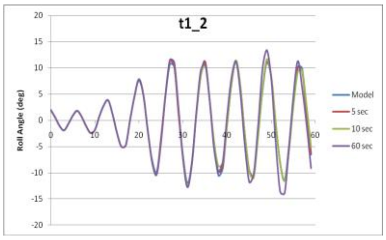
Constant Amplitude. Variable Frequency

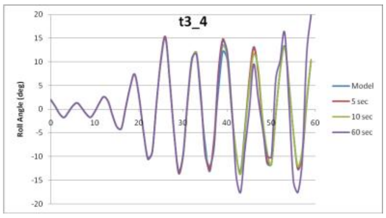
Here, the evaluation of the constant amplitude scenario is performed. An amplitude of 0.4 m was selected, while encounter frequency – natural roll frequency ratio was chosen between 1.987 and 2.504, which cover an area where resonance takes place at an intermediate intensity. Seven combinations of frequency and amplitude where chosen to generate the training time series, which include 320 training cases. These combinations are shown in Table 2 (Fi values). Three combinations were chosen as test cases, located between training values. Test cases are also shown in Table 2 (Fi_j values).

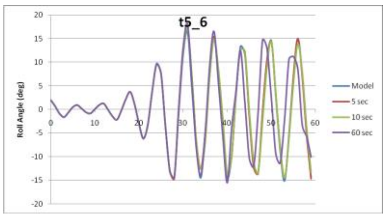
Table 2: Constant amplitude (0.4 m) case. Training and testing conditions

Case	$\omega_w\ (rad/s)$	$\omega_e\ (rad/s)$	ω_e/ω_n
F1	1,130	1,705	1,987
F1_2	1,145	1,735	2,022
F2	1,160	1,766	2,058
F3	1,190	1,827	2,130
F3_4	1,205	1,859	2,166
F4	1,220	1,890	2,203
F5	1,250	1,953	2,277
F5_6	1,265	1,985	2,314
F6	1,280	2,018	2,351
F7	1,310	2,083	2,427
F7_8	1,325	2,115	2,465
F8	1,340	2,148	2,504

The selected network architecture was a two hidden layer multilayer perceptron, with 30 neurons in each of the hidden layers. In the test cases, steady-state is reached in 60 seconds, so the time series are truncated there. In these cases, three predictions were performed for all of the three test cases: 5, 10 and 60 second predictions. As shown in the following figures, the results obtained from the three predictions are accurate enough to predict the appearance of the resonance phenomenon. The precision of the 60 second case is remarkable, as it accurately provides a prediction 40 seconds ahead in the four conditions tested.







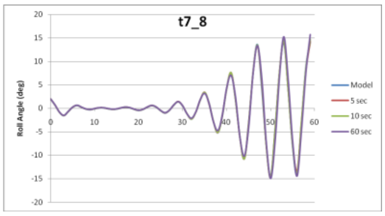


Fig. 4: Constant amplitude case. Predictions

Constant Frequency. Variable Amplitude

In this case, the evaluation of the constant frequency case is presented. A wave frequency of 1.085 rad/s was selected, which implies an encounter frequency of 1.615 rad/s and an encounter frequency-natural roll frequency ratio of 1.9. At this ratio, parametric rolling is expected between the amplitudes of 0.3 and 0.85 m. Training and test amplitudes were chosen between those values, considering six training time series (Table 3, Ai values) and two test series (Table 3, Ai_j values). These combinations generate 460 training cases. All the values are shown in Table 3. Again, a two hidden layer perceptron network architecture was selected, with 30 neurons in each of the hidden layers.

Table 3: Constant frequency ($\omega_e/\omega_n = 1.9$) case. Training and testing conditions

Case	$A_w\ (m)$
A1	0,30
A2	0,35
A3	0,40
A4	0,50
A4_5	0,55
A5	0,60
A6	0,70
A7	0,75
A7_8	0,80

A4_5 test case reaches steady-state in 60 seconds, and so it´s truncated in this value. Otherwise, case A7_8 is at the limit of the capsizing area, where chaotic behaviour and multiperiodicity start to take place and prediction is a lot more complicated [Neves *et ál.* (2009)]. This test case is not truncated, as steady-state is not well defined. In this case, three predictions were performed for the A4_5 test case, including 5, 10 and 60 second predictions. In test case A7_8, only 5 and 10 second predictions were performed, as a long term prediction is not possible in this chaotic scheme. In the following figures, the results obtained from test cases A4_5 and A7_8 are presented. Case A4_5 is accurate, and the time series forecast is very good in all of the three predictions. The results obtained in case A7_8 are not so good, but can be acceptable in the short term prediction case, taking in account the complexity of the behaviour of these kinds of systems.

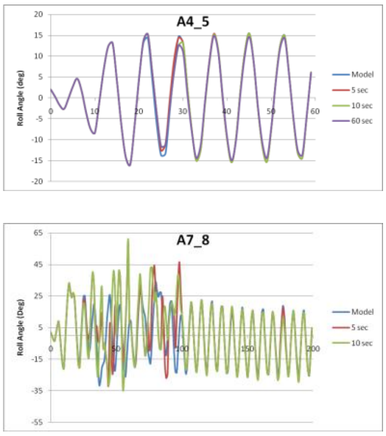


Fig. 5: **Constant frequency case. Predictions**

Variable Amplitude and Frequency

In this experiment, variable values for amplitude and wave frequency were chosen, defining the test area inside the instability region, but outside the chaotic areas where capsizing is most likely to occur. The amplitude ranges from 0.33 to 0.6 m, while the frequency ratio ranges from 1.917 to 2.504 rad/s. 49 combinations of amplitude and frequency were chosen for training, generating 2660 training cases. These combinations are shown in Table 4. With the described training process, the system should be able to predict the behaviour of the ship sailing in any of the wave conditions situated inside or in the surroundings of the rectangle limited by the aforementioned values. Test cases were chosen between these values; the five test combinations are presented in Table 5.

Table 4: **Variable amplitude and frequency case. Training cases. Combinations**

ω_w (rad/s)	ω_e (rad/s)	ω_e/ω_n	A_w (m)
1,100	1,645	1,917	0,33
1,140	1,725	2,011	0,36
1,180	1,807	2,106	0,42
1,220	1,890	2,203	0,48
1,260	1,975	2,302	0,54
1,300	2,061	2,402	0,57
1,340	2,148	2,504	0,6

Table 5: **Variable amplitude and frequency case. Test cases**

Case	ω_w (rad/s)	ω_e (rad/s)	ω_e/ω_n	A_w (m)
T1	1,200	1,848	2,154	0,46
T2	1,200	1,848	2,154	0,41
T3	1,320	2,104	2,453	0,345
T4	1,320	2,104	2,453	0,585
T5	1,240	1,932	2,252	0,52

The same architecture as in the previous cases was used; that is a multilayer perceptron, with two hidden layers and 30 neurons per layer. The five test cases have been truncated at 60 seconds and two predictions have been made, one for 5 seconds and another for 10 seconds. The results of the described tests are shown in Figure 6. As shown, the results are again very promising, although there are some punctual disturbances in cases T1, T3 and T5 and some difficulties for reproducing the model time series in case T4, as seen in case A7_8 (constant frequency). T4 is again (as A7_8) near the capsizing area, where chaotic and multiperiodic behaviour appears. Taking into account that most training cases are out of this area and that ship behaviour changes so drastically in these regions, the system is not so suitable for dealing with these cases.

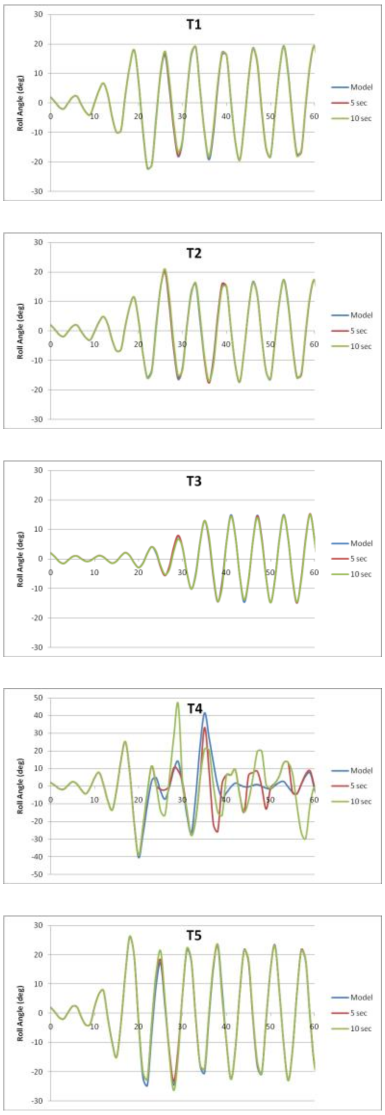


Fig. 6: **Variable amplitude & frequency case. 30 Neurons. Predictions**

It has to be said that the study of these cases is more complex than in the constant amplitude and frequency ones, as the number of training cases is bigger and the typology of the solutions more scattered. Taking this into account and also that the capacity of neural networks to deal with more complex functions increases with the number of layers and neurons in each of them, a new network, increasing the number of neurons in the hidden layers from 30 to 40, has been developed and tested. Again, as in the first case, the 49 training cases and 5 test cases were used, in order to evaluate also its capacity to deal with cases where chaos and multiperiodicity start to develop. The results are shown in Figure 7.

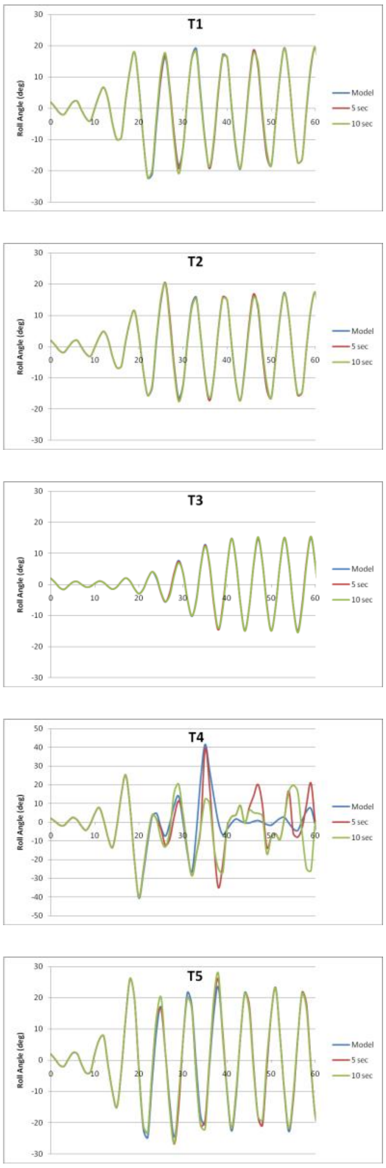


Fig. 7: Variable amplitude & frequency case. 40 Neurons. Predictions

The results obtained by increasing the number of neurons in the hidden layers are much better than those obtained with the 30 neuron cases, also including the mutiperiodic combinations. Although predictions in these last situations are still presenting divergences from the mathematical model, the results obtained in all the others are quite accurate and promising.

Roll Acceleration Analysis. Variable Amplitude and Frequency

Considering that our main objective is to predict the possible appearance of parametric rolling in the earliest possible stage, it is clear that by analyzing the ship roll acceleration we can know how the behaviour in roll is going to be before it happens. Therefore, we can use the aforementioned system to predict the ship roll accelerations and the possible appearance of high amplitude roll motions sooner that just by analyzing and predicting ship roll motions. This experiment was done in the same conditions as the last *Variable amplitude and frequency* one, that is, 49 training cases and 5 test cases and a two hidden layer perceptron network with 40 neurons each. Train and test cases were the same as in the mentioned experiment. The obtained results for the 5 and 10 seconds predictions show very good agreement between the model and the network outputs and also in the Test Case 4, where multiperiodicity appears.

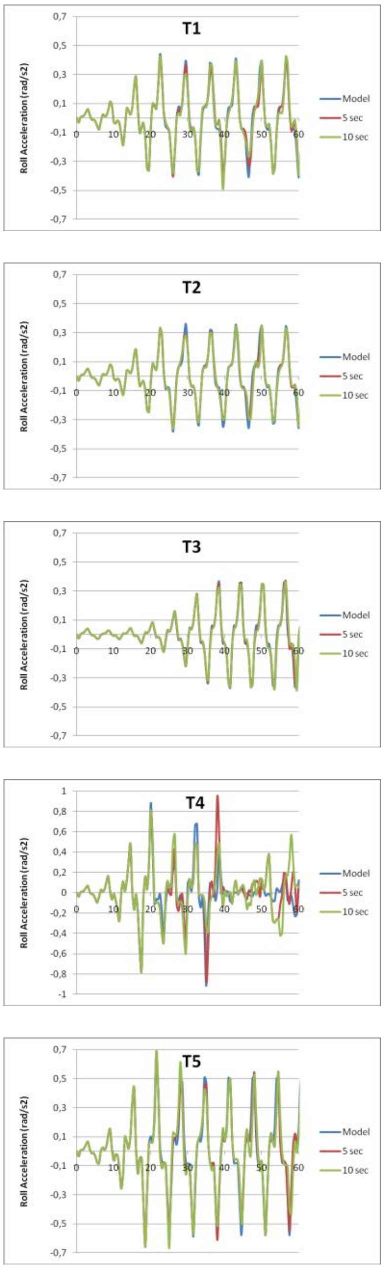


Fig. 8: Acceleration analysis. Variable amplitude & frequency case. 40 Neurons. Predictions

Conclusions

The present work presented an application of artificial neural networks to ship behaviour prediction. Ship motions were simulated using a three degree of freedom mathematical model, where heave, roll and pitch motions are obtained in a coupled way. This model has been proven to accurately represent the parametric rolling phenomenon. The case under study is a transom stern fishing vessel with a high tendency to easily develop parametric roll resonance. Different scenarios were considered in order to evaluate the capacity of neural networks to predict future ship rolling motions from the analysis of a given portion of a roll motion or acceleration time series. These scenarios include constant wave amplitude conditions and variable wave frequency, variable amplitude and constant frequency and both variable parameters, all of them placed inside the area where parametric rolling is most likely to occur. In those cases, a multilayer perceptron neural network was used to make predictions 5 and 10 seconds in advance from a series of 20 seconds input, obtaining very promising results in most cases. Improvement of the system performance shall be achieved in order to accurately deal with situations close to capsizing, where chaotic and multiperiodical responses take place and also to increase the forecasting time to more than those 5 or 10 seconds.

The results obtained with the approach presented will be very useful for the development of a parametric rolling detection and prevention system. This system should analyse the forecasted roll motion time series obtained with this neural network system and decide if a parametric rolling process is going to occur. Current work is being done in order to define the parametric roll onset criteria. It is clear that increasing the forecasted time (only dependent on the type and configuration of the network used and the complexity of the analysed condition), will also increase the time crew will have to take corrective actions or to activate an automatic prevention system, which would take these actions by itself. The results obtained with a mathematical model and longitudinal waves, should now be completed with the irregular wave case and also with model tests, in order to evaluate the performance of a neural network trained with a numerical model to predict the motions of a real ship. The transition cases between resonant and non-resonant areas will also be studied.

Acknowledgement

The present work was supported by the Spanish Ministry of Education under the FPU program, grant AP2006-03211 and by MICIIN project TRA2009-13805 and Xunta de Galicia project 08DPI011CT.

The last author acknowledges the financial support of CNPq for the STAB Project (Nonlinear Stability of Ships).

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