On the Application of Artificial Neural Networks for the Real Time Prediction of Parametric Roll Resonance

Marcos Míguez González, Vicente Díaz Casás, Fernando López Peña, and Luis Pérez Rojas

Abstract In this paper, the practical implementation methodology of an artificial neural network (ANN) based parametric roll prediction system, is studied. In order to avoid expensive scale tests, an uncoupled nonlinear roll model is applied to tune the system. The capability of this model to accurately simulate the phenomenon of parametric roll resonance is validated using towing tank tests. Finally, the behavior of the ANN system for forecasting roll motion in a realistic sailing condition has been investigated, obtaining very promising results.

Keywords Parametric rolling · Neural networks · Time series forecasting · Ship stability

1 Introduction

Fishing represents one of the industrial sectors where occupational accidents are more frequent. In fact, fishing is considered as one of the most dangerous activities worldwide. Data from several sources indicate that it is among the first ranked activities in fatal injury rates, including different European countries or the US [1–3].

Most of the human losses occur due to ship related events, such as stability issues, grounding, falling objects, etc. Among them, incidents due to stability failures (i.e. capsize or large heel) account for the majority of the casualties, especially in small

M. Míguez González (✉) · V. Díaz Casás · F. López Peña
Integrated Group for Engineering Research, Ferrol Industrial Campus, University of A Coruña, A Coruña, Spain
e-mail: marcos.miguez@udc.es

V. Díaz Casás
e-mail: vicente.diaz.casas@udc.es

F. López Peña
e-mail: fernando.lopez.pena@udc.es

L. Pérez Rojas
Model Basin, ETSIN, Technical University of Madrid, Madrid, Spain
e-mail: luis.perezrojas@upm.es

K. J. Spyrou et al. (eds.), *Contemporary Ideas on Ship Stability*, Fluid Mechanics and Its Applications 134, https://doi.org/10.1007/978-3-031-16329-6_20

ships. This could be explained by the fact that very often these accidents develop very fast and because they usually imply the complete loss of the vessel [4].

Small and medium length vessel skippers base their capability for evaluating the stability of their ships mainly on previous experience, which usually does not include important incidents. In addition, they lack training for adequately understanding the information contained in the stability booklets, which are, if available, the only help they have for evaluating the intact static stability of the ship in a given sailing condition. An even more dramatic situation shows up when talking about dynamic stability issues. Considering that in most cases these phenomena are completely unknown to the skippers, it is impossible that they could face them correctly in order to avoid their consequences. All these issues, together with the fact that they need to fish even under very rough weather conditions and other circumstantial factors, are the main causes of such accidents.

Stability guidance systems were developed to try to mitigate this situation, providing the crew with stability-related information. Traditionally, they have ranged from stability posters to computer approaches, which considered only a limited set of conditions or relied in subjective data provided by the crew [5]. However, in recent years these systems started pointing towards the so called "second generation guidance systems", which in addition to the characteristics of the previous ones, also use real time data acquisition and analysis to determine the stability characteristics of the vessel and to provide objective and more precise information to the crew.

In this last group, some of the authors of this work have proposed their own alternative (Fig. 1). This system provides the minimum essential information related to the stability of the vessel in the current loading condition, in a very clear and understandable way, even for users with no specific training in the use of computer software [5, 6]. Although it was initially based only on the computation of static stability criteria from loading condition data introduced in the system by the crew, in the last years the authors have been working on implementing additional real-time capabilities. These included the automatic estimation of the stability parameters of the vessel during operation [7] and the detection of the onset of parametric roll resonance. And is in this last functionality where this work is focused.

As it is well known, parametric roll is a phenomenon which affects fishing vessels, among other types of ships, and that may generate very large amplitude roll motions in a very sudden way, leading to heavy damage or even capsizing [8].

The main objective of the proposed prediction system is to alert the crew about the immediate appearance of an episode of parametric rolling and to allow them to take preventive actions. This approach is based on the use of artificial neural networks (ANN). These are biologically inspired algorithms, which after a training process with a set of samples, are capable of reproducing the behavior of nonlinear systems [9]. ANN have been widely used as forecasters in different fields, including ship roll motions (e.g. [10]). In previous works, the authors have tested the performance of this approach with some success, both using as training and testing cases roll motion data obtained from a three degrees of freedom mathematical model [11] and from a more realistic approach using towing tank tests in head seas [12].

Fig. 1 Fishing vessel stability guidance system screenshot

However, when it comes to the practical implementation of such a system in a fishing vessel, there are some economic constraints that have to be taken into account. Carrying out a large campaign of towing tank tests for obtaining the training data, needed to accurately set up the ANN detector, implies a large cost and complicates the adaptation of the system to each ship, especially in the case of a small or mid-sized fishing vessels. So, in order to overcome this issue, an alternative approximation is presented in this work. In order to reduce the cost of fitting the system to each ship, a simple 1.5 degrees of freedom nonlinear mathematical model has been proposed as the source of training data, instead of using more expensive towing tank tests data or more complex mathematical codes. The performance of this model itself to accurately reproduce the roll motion of a medium sized trawler has been validated by using data from towing tank tests. And finally, the performance of the mathematical model-tuned ANN forecasting system to predict the appearance of parametric roll in a realistic seaway is evaluated. In order to do this, some results from the application of the ANN forecaster to a set of roll motion time series obtained from towing tank tests, are presented. This work updates and complements the findings previously described by Míguez González et al. [13].

2 Model Tests

The ship under analysis is a medium sized stern trawler having an acute tendency towards developing parametric roll resonance even in not very heavy seas. This trend is caused, in part, by its transom stern hull forms and bow flare. This ship has also been studied by de Juana Gamo et al. [14], and a very similar one by Míguez González and Bulian [15]. Its main characteristics are described in Table 1, and its bodyplan is included in Fig. 2. A 1/18.75th scale model has been used for the towing tank experiments, which arrangement is also shown in Fig. 2. It is important to note that, although this type of vessels are usually equipped with bilge keels, in this case the vessel under consideration has no bilge keels installed.

These scale model tests have been carried out in the ETSIN test basin (Technical University of Madrid). The scale model has been restrained as to ensure that surge, sway and yaw are limited, while leaving the model to heave, roll and pitch freely. All tests have been done in longitudinal head regular waves. Considering that the main parameter affecting the appearance of parametric roll resonance is the wave encounter frequency to natural roll frequency ratio (ω_e/ω_0), and the fact that parametric roll resonance could be expected for ratios between 1.9 and 2.2 and even more, tests included ratios ranging between 1.7 and 2.3. Regarding wave height (H_w), tests included values between 0.5 m and 3 m. Finally, four ship speeds, corresponding to Froude numbers (Fn) 0, 0.1, 0.2 and 0.3, have been considered. The complete test matrix is composed of 24 different combinations for the zero speed case, 16 for Fn 0.1, 15 for Fn 0.2 and 13 for the Fn 0.3. These conditions include cases where parametric roll resonance develops and others where it does not. Wave length

Table 1 Test vessel main characteristics

Overall length	34.50 m
Length between perpendiculars	29.00 m
Beam	8.00 m
Depth	3.65 m
Draft	3.290 m
Displacement	448 t
Metacentric height (GM)	0.350 m
Natural roll frequency (ω_0)	0.563 rad/s
Dry roll gyradius w.r.t. CoG (k_{xx})	3.128 m (39.1% B)

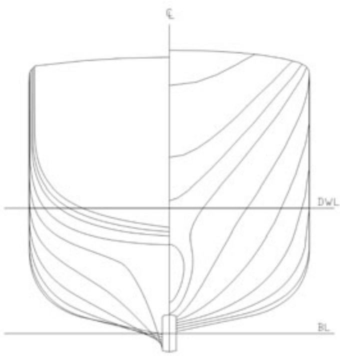

Fig. 2 Hull bodyplan (left) and scale model towing tank tests arrangement (right)

(λ_w) is determined as a function of wave frequency (ω_w), under the deep water approximation. In addition, still water roll decay tests have also been accomplished at four different forward speeds (corresponding to Froude numbers 0, 0.1, 0.2 and 0.3) and different initial roll angles. These decay tests were also used to estimate the dry roll gyradius of the vessel with respect to the centre of gravity, included in Table 1. In order to obtain this value, the added inertia in roll at the natural roll frequency was estimated by using a potential theory code. A complete description of this campaign, including detailed procedures, results and their analysis, could be found in Míguez González [16].

3 Mathematical Model

In order to tune the prediction system in a simple and inexpensive way, it was necessary to define a mathematical model able to adequately reproduce the behaviour of the ship in parametric roll conditions, but minimizing the number of parameters that have to be computed to fit the model to other different vessels.

In this work, the 1 degree of freedom (d.o.f.) nonlinear uncoupled roll model proposed by Bulian [17] has been adopted. On it, the time varying nonlinear roll restoring term needed for triggering parametric roll is computed taking into account the quasi-statical effects of heave and pitch motions in roll. This leads to considering this model as a 1.5 degrees of freedom approach, having the following structure:

$$(I_{xx} + A_{44}) \cdot \ddot{\phi} + B_{44,T}(\dot{\phi}) \cdot \dot{\phi} + C_{44}(\phi, t) = 0 \tag{1}$$

where I_{xx} and A_{44} are respectively the mass and added mass moments of inertia in roll, $B_{44,T}(\dot{\phi})$ represents the nonlinear damping term and $C_{44}(\phi, t)$ is the time varying nonlinear restoring coefficient ($C_{44}(\phi, t) = \Delta \cdot GZ(\phi, t)$). As it is generally accepted, the added mass term A_{44} has been obtained by potential theory methods. The computation of restoring and damping terms is described in the following subsections.

3.1 Restoring Arm

As mentioned above, the influence of pitch and heave motions, together with wave passing along the hull, has to be taken into account for an accurate simulation of parametric roll. Considering that the proposed model doesn't explicitly include the coupling between roll and heave and pitch, both effects have been taken into account in a quasi-static way within the restoring term.

In order to do this, the "look up table" approach, described by Bulian [17] and applied by many authors to different types of ships [18], recommended by class societies for modelling the variation of the ship restoring capabilities in longitudinal waves [19] and included within the Second Generation Intact Stability Criteria Level 2 vulnerability assessment for parametric roll [20], was applied for computing the restoring term $C_{44}(\phi, t)$.

Under this approach, for each wave crest position and roll angle, trim and sinkage are statically balanced. This method has demonstrated to perform well in following seas and in head seas with wavelengths longer than ship length (where heave and pitch motions are supposed to be quasi-static). Additionally, in Bulian [17], its application to the head seas case in wavelengths similar to ship length, was also successful.

For each set of wave parameters (height and wavelength) and for the different positions of wave crest along the hull, the *GZ* curves were computed applying classical hydrostatics under free trim conditions. In order to obtain the time dependant restoring coefficient $C_{44}(\phi, t)$, the aforementioned wave crest domain *GZ* curves, were transformed to the time domain by considering the wave encounter frequency.

An example of the results of these *GZ* computations are displayed and compared to the still water case in Fig. 3. Additionally, the interpolated *GZ* surface for this same case and the different wave crest positions is also presented.

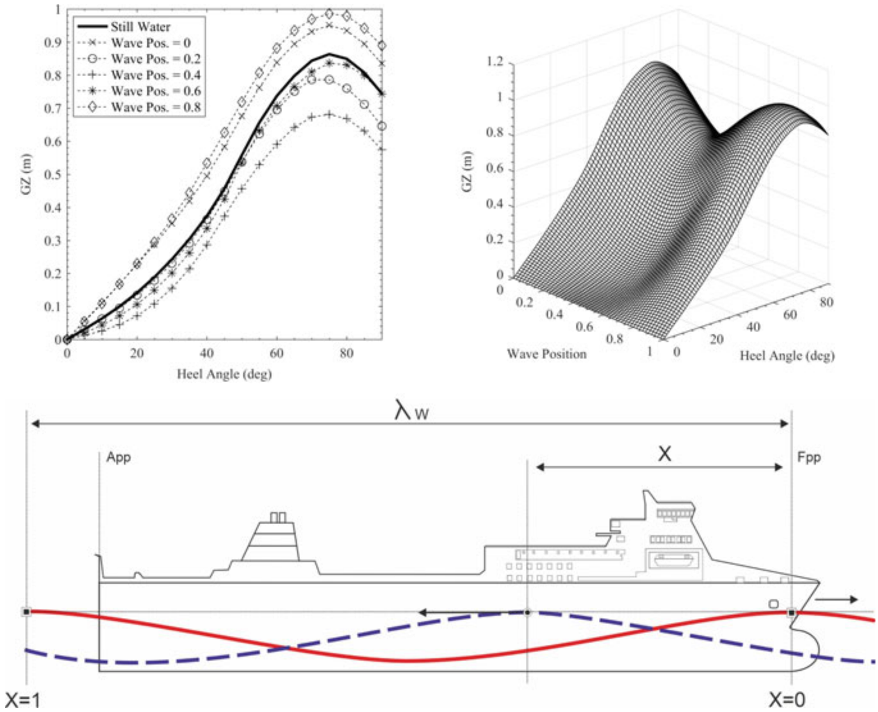

Fig. 3 Top Left: *GZ* curves as a function of wave position. Top Right: *GZ* variation due to wave passing. $\lambda_w = 40$ m. $H_w = 2$ m. Bottom: Wave position (X) along the hull. X = 0, wave crest at the forward perpendicular. X = 1, wave crest λ_w m away from the forward perpendicular

3.2 Roll Damping

One of the most critical elements for ensuring a good simulation of parametric roll resonance is the modelling of roll damping, as it is highly nonlinear in the large roll amplitudes present during parametric resonance. In order to account for these nonlinearities, a nonlinear quadratic approach has been adopted, decomposing roll damping in a linear and a quadratic term. This same approach has been broadly applied in other works dealing with parametric roll modeling, (e.g. [21]). According to this structure, the ship roll damping would read:

$$B_{44,T}(\dot{\phi}) \cdot \dot{\phi} = B_{44a} \cdot \dot{\phi} + B_{44b} \cdot \dot{\phi} \cdot \left|\dot{\phi}\right| \tag{2}$$

In order to obtain the linear ($B_{44,a}$) and quadratic ($B_{44,b}$) coefficients, still water roll decay tests for different forward speeds and initial roll angles have been carried out. The procedure followed for determining the damping coefficients from these tests, is the one described in Himeno [22]. In Fig. 4, the results of roll decrement (obtained between subsequent full cycles) as a function of mean roll angle are presented, together with a quadratic fitting for the whole set of data points obtained in the roll decay tests at the four tested forward speeds.

In adittion, in Table 2, the obtained damping coefficients at the four Froude numbers are shown in the form of non-dimensional damping coefficients, defined by:

$$2 \cdot \nu \cdot \omega_{\phi} = \frac{B_{44a}}{(I_{xx} + A_{44})}; \;\; \beta = \frac{B_{44b}}{(I_{xx} + A_{44})} \tag{3}$$

The validation of the damping coefficient results has been done by comparing the towing tank results of the roll decay tests to those obtained by using the mathematical model. Results presented in Fig. 5, corresponding to forward speeds of Fn

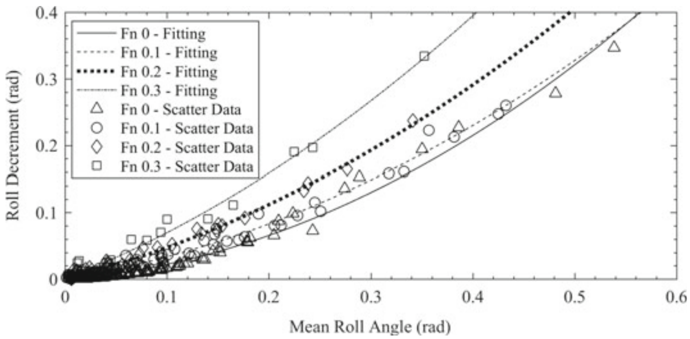

Fig. 4 Roll decrement data (scatter points) and fitting quadratic polynomial (lines) from roll decay tests

Table 2 Non-dimensional damping coefficients

Froude number (Fn)	ν [−]	β [rad^{-1}]
0	0.0187	0.3932
0.1	0.0404	0.3008
0.2	0.0620	0.3158
0.3	0.0953	0.3631

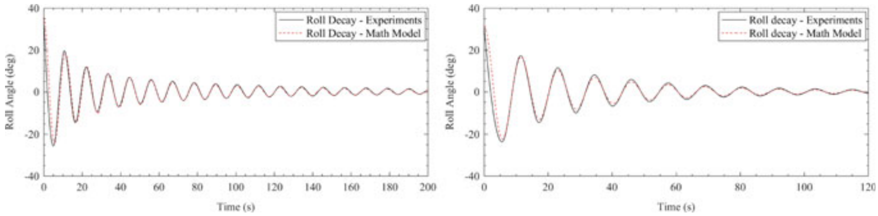

Fig. 5 Roll decay tests. $Fn = 0$ (left) and $Fn = 0.1$ (right)

0 and 0.1, show that the roll damping model is adequate, accurately reproducing the experimental roll decay tests.

3.3 Model Validation

In this section, the performance of the model for accurately simulating the roll motion of the studied vessel in the different sailing conditions, including those where parametric rolling is present, is analyzed. The data used for the validation process are those obtained from the towing test campaign that has been already described, including runs at different forward speeds, wave frequencies and wave heights.

In Fig. 6, two sample comparisons between the simulations and the towing tank tests, are presented. On them, the roll motion time series obtained with the proposed mathematical model, for conditions likely to induce parametric roll, are compared to the corresponding results from the towing tank experiments. These conditions include $\omega_e/\omega_0 = 2$, wave height H_w of 1.491 m and forward speeds corresponding to Fn 0 and 0.1. A full description of the results from the whole test matrix is available in Míguez González [16].

Observing these results, it can be concluded that the correspondence between simulated and towing tank test data is quite good, both in the initial transient stage and in the steady state motion; however, a slight underestimation of the roll amplitude has been observed, not only in the two presented cases, but also in the rest of the compared time series at these two speed values.

This issue is more noticeable as speed increases, as could be appreciated in the right side of Fig. 6; in fact, the model is unable to reproduce any of the parametric

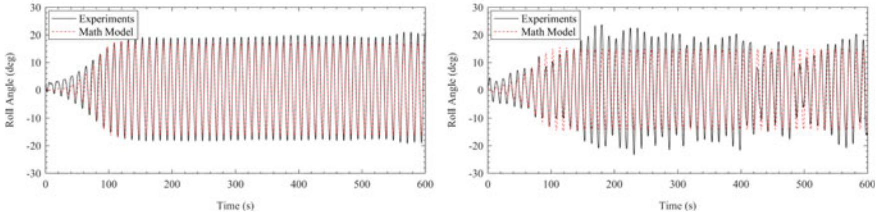

Fig. 6 Comparison between experimental roll motion and 1.5 d.o.f. model simulations. Left: $Fn = 0$. $\omega_e/\omega_0 = 2.0$. $H_w = 1.491$ m. $\lambda_w = 48.640$ m. Right: Fn = 0.1. $\omega_e/\omega_0 = 2.0$. Hw = 1.491 m. $\lambda = 66.145$ m

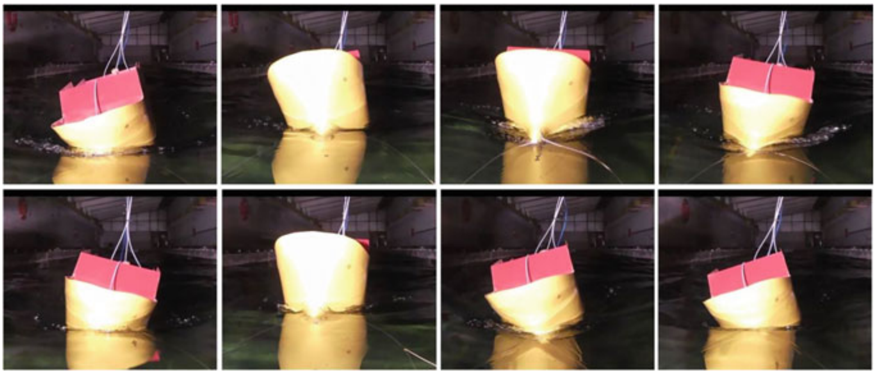

Fig. 7 Detail of pitch motions during one roll cycle under the effect of parametric roll. $Fn = 0.2$. $\omega_e/\omega_0 = 2.0$. $H_w = 1.988$ m. $\lambda_w = 81.965$ m

roll events which occur for the higher speeds of *Fn* 0.2 and *Fn* 0.3, where lower wave frequencies imply much longer wavelengths [16].

This behavior may be related with the quasi static approach adopted for the computation of the time varying restoring term. From the towing tank tests experiments, it has been observed that heave and pitch motions were of quite large amplitude in these conditions (see Fig. 7), and that their influence in the developing of parametric roll was much higher than that predicted by the quasi static approach. However, and in order to illustrate the performance of the parametric roll prediction system, only conditions of up to *Fn* 0.1, where the mathematical model has demonstrated to work fine, have been used.

4 Parametric Roll Forecasting System

Developing a system which could alert the crew and allow them to take corrective actions before a parametric roll event takes place, is a task which has gained a lot of attention in the last years, due to the increase in size and number of ships likely to suffer from the phenomenon, especially containerships. Among the published alternatives, the one by Galeazzi et al. [23, 24] is the only under real scale testing nowadays.

On the other hand, the authors of the present work have been working on the development of a roll forecasting system, based on the application of Artificial Neural Networks (ANN). The main objective of this approach is to predict, some time in advance, the roll motion time series of the vessel, including possible episodes of parametric roll resonance. In comparison to the single detection provided by the proposal by Galeazzi et al. [23], the availability of the roll motion time series forecast which provides the ANN approach, has the main advantage of increasing the performance of possible corrective actions [12].

The structure of an ANN consists of an input layer, which receives the data, a series of hidden layers, where the so-called neurons are included, and an output layer. Neurons are in charge of processing the data by weighing, biasing and summing up the input data they receive, processing them with an activation function and sending them to the following neuron. The process of training consists of feeding the network with known data of the behavior of the system to be modeled, and selecting the weights and biases which minimize the errors between real and predicted outputs [25], modifications which are done relying in the so called learning algorithm. In this work, a multilayer perceptron architecture (MPNN) has been selected, which is shown in Fig. 8. MPNN are also called feedforward or backpropagation networks, as they use the error backpropagation algorithm for the update of weights and biases [9].

The process for obtaining the outputs of this network from the corresponding inputs, is summarized in Eqs. 4 and 5. Basically, in each neuron k, each imput x_j is weighted by a synaptic weight w_{kj} and all the weighed inputs of the neuron are added, together with a bias b_k. The obtained result v_k, known as activation potential, is proccesed by an activation function *f()*,obtaining the neuron output y_k. This activation function is selected depending on the type of problem and data under consideration, and it keeps the output of the neuron under some desired limits. Finally, and regarding the number of hidden layers and neurons of an ANN, it has to be said that it determines the degree of complexity of the problems which could be tackled by the network, but only up to a specific threshold. From that point onwards, the capabilities of the system are not improved although the number of neurons or hidden layers is increased.

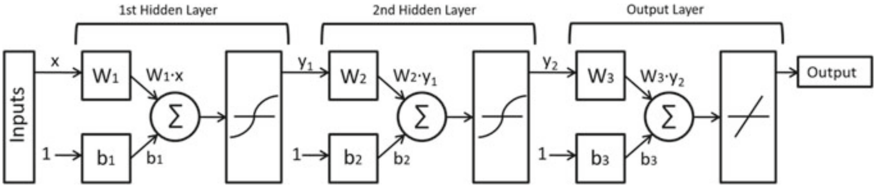

Fig. 8 Multilayer perceptron artificial neural network architecture

$$v_k = \sum_{j=1}^{m} w_{kj} x_j + b_k \tag{4}$$

$$y_k = f(v_k) \tag{5}$$

As it has been already described, the objective of this work is to evaluate the performance of a roll motion forecaster based on the use of ANN, which have been trained using a simplified nonlinear mathematical model of roll motion. This would reduce the cost of adapting the system to each vessel, as the setting up of the mathematical model is a simpler task than developing a whole scale model test campaign. This way, the only need when setting up the system on a ship will be to compute the mathematical model parameters and then use it to train the networks, with no need for complex towing tank testing. This approach would represent the practical way of implementing the system in a real case.

After some previous testing, which is described in detail in Míguez González [16], it was concluded that the structure with a better compromise between simplicity and performance, is that of a multilayer perceptron network with three hidden layers, 30 neurons per layer, and one output layer. The input vector is composed by 40 elements, representing 20 s of the roll motion time series. The output is composed by only one element, being it the prediction one step ahead. Substituting the output value within the input vector and recursively executing the algorithm, predictions in different degrees of advance can be obtained. Tan sigmoid-functions have been used as activation functions in the hidden layers and a piecewise linear function has been selected for the output layer.

Regarding the training algorithm, its objective is to modify the different weights and biases in order to optimize a given performance (loss) function. In this case, the error between the network's prediction and the target value, measured using the Mean Squared Error, has been selected as performance function. In the case of the training algorithm, the Levenberg–Marquardt (L–M) algorithm [26] has been used. In Fig. 9, the evolution of the MSE during the subsequent training epochs for the best performing network is shown. In this case, training was stopped when the obtained MSE value was below the goal value of 1×10^{-8}.

The training data was obtained from 56 time series of roll motion, obtained with the 1.5 d.o.f. nonlinear mathematical roll model previously described, at different combinations of wave frequency and height and for a forward speed of *Fn* 0.1. The selected parameters are included in Table 3. This data set not only includes cases where resonance is most likely, but also combinations of parameters where resonance does not develop.

Regarding training, it has to be taken into account that the first set of weights and biases are randomly generated at the beginning of the process; so, the same set of training cases could lead to trained networks with different performance. In order to improve the obtained results, 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.

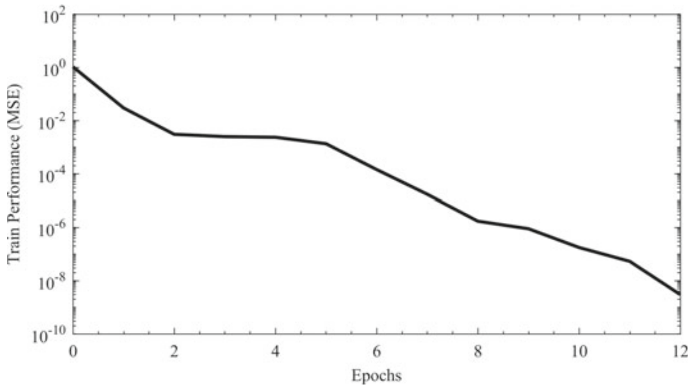

Fig. 9 Evolution of MSE with epochs during the training process. Best performing network

Table 3 Training data parameters

Froude number *Fn*	0.1
ω_e/ω_0 range	1.6–2.6
H_w range	0.5–2.5 m

In order to test the system, two time series, where parametric roll takes place, have been selected from the towing tank tests described in preceding sections. The parameters of these time series are included in Table 4. In both cases, the forecasting system has been executed to obtain predictions 10 s ahead, which approximately represent one whole roll period. The obtained results are presented in Fig. 10. The Mean Squared Error (MSE) of the predictions is included also in Table 4.

Analyzing the obtained results, it can be observed that the forecasting system correctly tracks the onset of the phenomenon in both test cases. However, as roll motion amplitude increases, some overpredictions are observed, which are especially relevant in Test Case 1. If the system is applied only for detecting the appearance of the phenomenon, these overpredictions won´t be very relevant, as they won't imply a misdetection or false alarm. Nevertheless, if forecasted roll motion is needed for establishing preventive measures, it is necessary to improve the performance of the system in order to avoid these peaks in the predicted roll motion.

Table 4 Test data parameters and MSE results

	Test case 1	Test case 2
Froude number *Fn*	0.1	
ω_e/ω_0	2.0	
H_w (m)	1.491	1.988
MSE $\times 10^{-4}$	442.00	504.14

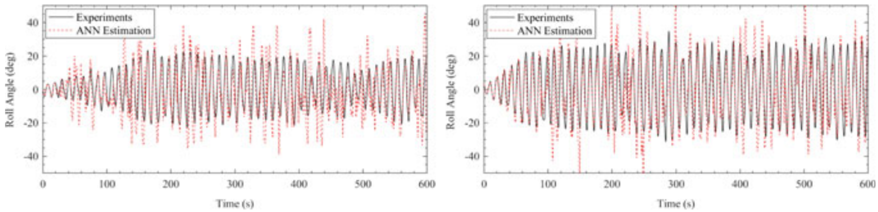

Fig. 10 Prediction results. Test Case 1 (left) and Test Case 2 (right)

5 Conclusions

This work presents some of the activities carried out by the authors for implementing a parametric roll prevention system based on the use of Artificial Neural Networks within an onboard stability guidance software. This system is primarily focused on providing stability information to the skipper of small and medium sized fishing vessels. The main requirements of such a system are ease of use and installation, and low cost. These requirements make the use of towing tank test campaigns not a feasible option for training the forecaster. The presented approach relies on the use of a mathematical model to train the ANNs for forecasting roll motion in realistic sailing conditions.

In order to do this, a one degree of freedom nonlinear roll model of a medium sized trawler, where pitch and heave effects on roll are taken into account in a quasi–static way has been developed. Moreover, a nonlinear quadratic approximation of roll damping term has been selected. The capacity of this model to accurately reproduce parametric roll resonance in different conditions of wave frequency, wave height and ship forward speed, has been analyzed by comparing the results obtained with the model against those obtained from a towing tank test campaign. In addition, roll decay tests in still water have been carried out to define the components of the quadratic damping.

The proposed model has shown a good performance for simulating parametric rolling at small forward speeds (up to *Fn* 0.1). However, at higher speeds the model is unable to simulate the large coupling between heave, roll and pitch observed in the tank tests and the parametric rolling events that were observed in them.

Once the model behaviour has been analyzed, it has been applied for computing the ANN training data, including different combinations of wave parameters. The selected speed corresponds to a *Fn* 0.1, at which the proposed forecasting model showed to be accurate.

With the objective of testing the system in a realistic situation, two time series where parametric roll is completely developed, have been selected from the *Fn* 0.1 tank test results and the forecaster was executed in order to obtain 10 s in advance predictions. The obtained forecasts are quite accurate in both test cases, especially during the transient period in which resonance develops, although some overpredictions were observed during the steady state phase.

Regarding the prediction horizon, it is necessary to improve this value because 10 s (1 roll period) could be enough for triggering automatic corrective actions in the type of vessels analyzed in this work; but they seem to be too short if these corrective actions have to be undertaken by the crew.

In any case, the obtained results empower the idea of applying mathematical model trained artificial neural networks, for parametric roll prediction, with no need of expensive and time consuming towing tank tests. Nevertheless, further research is needed to improve the performance of the forecaster during the steady state phase, and also to increase the prediction time horizon.

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

References

1. Bureau of Labor Statistics (BLS) (2014) National census of fatal occupational injuries in 2013. Bureau of Labor Statistics, U.S. Department of Labor
2. Jensen OC, Petursdottir G, Holmen IM, Abrahamsen A, Lincoln J (2014) A review of fatal accident incidence rate trends in fishing. Int Marit Health 65(2):47–52
3. MESS (2014) Estadística de Accidentes de Trabajo. Ministerio de Empleo y Seguridad Social. Subdirección General de Estadísticas, Gobierno de España, Madrid, Spain
4. Mata-Alvarez-Santullano F, Souto-Iglesias A (2014) Stability, safety and operability of small fishing vessels. Ocean Eng 79:81–91
5. Santiago Caamaño L, Míguez González M, Díaz Casás V (2018) Improving the safety of fishing vessels through roll motion analysis. In: Proceedings of the 37th ASME international conference on ocean, offshore and arctic engineering (OMAE 2018), Madrid, Spain
6. Míguez González M, Caamaño Sobrino P, Tedín Álvarez R, Díaz Casás V, Martínez López A, López Peña F (2012) Fishing vessel stability assessment system. Ocean Eng 41:67–78
7. Santiago Caamaño L, Galeazzi R, Nielsen UD, Míguez González M, Díaz Casás V (2019) Real time detection of transverse stability changes in fishing vessels. Ocean Eng 189:106369
8. Ghamari I, Greco M, Faltinsen OM, Lugni C (2020) Numerical and experimental study on the parametric roll resonance for a fishing vessel with and without forward speed. Appl Ocean Res 101:102272
9. Golden R (1996) Mathematical methods for neural network analysis and design. The MIT Press
10. Yin JC, Zou ZJ, Xu F (2013) On-line prediction of ship roll motion during maneuvering using sequential learning RBF neural networks. Ocean Eng 61:139–147
11. Míguez González M, López Peña F, Díaz Casás V, Galeazzi R, Blanke M (2011) Prediction of parametric roll resonance by multilayer perceptron neural network. In: Proceedings of the 21st international offshore (ocean) and polar engineering conference (ISOPE 2011), Maui, EEUU
12. Míguez González M, Díaz Casás V, López Peña F, Pérez Rojas L (2012b) Experimental parametric roll resonance characterization of a stern trawler in head seas. In: Proceedings of the 11th international conference on the stability of ships and ocean vehicles, Athens, Greece
13. Míguez González M, Díaz Casás V, López Peña F, Pérez Rojas L (2013) Experimental analysis of roll damping in small fishing vessels for large amplitude roll forecasting. In: Proceedings of the 13th International Ship Stability Workshop, Brest, France

14. De Juana Gamo J, Arias Rodrigo C, Pérez Rojas L (2005) On the parametric rolling of fishing vessels. In: Proceedings of the 1st international conference on marine research and transportation
15. Míguez González M, Bulian G (2018) Influence of ship dynamics modelling on the prediction of fishing vessels roll response in beam and longitudinal waves. Ocean Eng 148:312–330
16. Míguez González M (2012) A study of ship parametric roll resonance for the evaluation of preventive strategies. PhD Thesis, University of A Coruña, A Coruña, Spain
17. Bulian G (2006) Development of analytical nonlinear models for parametric roll and hydrostatic restoring variations in regular and irregular waves. PhD Thesis, Universitá Degli Studi di Trieste, Trieste, Italy
18. Bačkalov I, Bulian G, Cichowicz J, Eliopoulou E, Konovessis D, Leguen JF, Rosen A, Themelis N (2016) Ship stability, dynamics and safety: status and perspectives from a review of recent STAB conferences and ISSW events. Ocean Eng 116:312–349
19. American Bureau of Shipping (ABS) (2004) Guide for the assessment of parametric roll resonance in the design of container carriers
20. IMO (2019) SDC 7/WP.6. Finalization of second generation intact stability criteria; report of the drafting group on intact stability. International Maritime Organization, London, UK
21. Neves MAS, Rodríguez CA (2006) On unstable ship motions resulting from strong non-linear coupling. Ocean Eng 33:1853–1883
22. Himeno Y (1981) Prediction of ship roll damping. A state of the art. The University of Michigan College of Engineering, Michigan, USA, Department of Naval Architecture and Marine Engineering
23. Galeazzi R, Blanke M, Poulsen NK (2012) Early detection of parametric roll resonance on container ships. IEEE Trans Control Syst Technol 21(2):489–503
24. Galeazzi R, Blanke M, Falkenberg T, Poulsen NK, Violaris N, Storhaug G, Huss M (2015) Parametric roll resonance monitoring using signal-based detection. Ocean Eng 109:355–371
25. Haykin S (1999) Neural networks: a comprehensive foundation. Prentice Hall
26. Demuth H, Beale M, Hagan M (2011) Neural network toolbox™ 6. user's guide. The MathWorks Inc., Natick, MA, USA