RECURSIVE NEURAL NETWORK MODEL OF CATAMARAN MANOEUVRING

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SUMMARY

A neural network model to simulate catamaran manoeuvres is proposed as an alternative to the traditional methodology of developing manoeuvring mathematical models. Data obtained in full-scale trials with a real ship are used to train the model. By recording full-scale trials of catamaran manoeuvres it is possible to generate a neural network model which will allow the prediction of the catamaran manoeuvring performance under different conditions.

A Recursive Neural Network (RNN) manoeuvring simulation model is proposed and applied to a catamaran in this specific case. Inputs to the simulation are the orders of rudder angle and ship's speed and also the recursive outputs velocities of sway and yaw. Two types of manoeuvres are simulated: tactical circles and zigzags. The results between the full-scale data and the simulations are compared in order to analyze and determine the accuracy of the RNN. The study is performed for a catamaran operating in the Tagus estuary for passenger transport to and from Lisbon.

1. INTRODUCTION

Traditional mathematical models are usually applied to simulate nonlinear systems and high accuracy is expected from the obtained results. However, the nonlinearities of the system are usually very difficult to model and inefficient from the computational point of view. The approach adopted sometimes is to approximate the nonlinear model by a linear one. However, the results of the simulations obtained from the approximate linear model loose accuracy [1].

However, accurate performance prediction is an essential capability for ship designers and builders. Through parameters inherent to the manoeuvrability model that describes the performance of certain ship, one can develop and validate tools either for predicting or measuring its behaviour [2].

The motivation of the work presented here is to describe an alternative and efficient approach to model non-linear systems based on artificial neural networks (ANNs) applied to manoeuvring simulation of ships, and in this particular case to catamarans.

ANNs have been successfully applied to a variety of problems in naval architecture, in particular in modelling empirical data to be used in marine design and analysis [3]. For instance, simulations using ANNs have been made using data from both model and full-scale submarine manoeuvres. The incomplete data measured on the full-scale vehicle was augmented by using feed-forward neural networks as virtual sensors to intelligently estimate the missing data [4]. The creation of simulations at both scales allowed the exploration of scaling differences between two vehicles [5].

Another example of marine application of ANNs is made in catamarans or trimarans with unusual underwater shape, which experience significant non-linearity's when the vessel motions are large in magnitude. ANN techniques have been used to complement a time-domain numerical model for prediction of pitch and heave motions of a catamaran design [6], and a trimaran in regular head seas [7, 8, 9]. Zhang et al [10] present a back-propagation-based neural network controller. The principal intention is to take advantage of the learning ability of neural networks, and to derive an autonomous neural control algorithm which is independent of the mathematical model of the ship.

The objective of the development of a manoeuvring simulator for surface ships is to reproduce the vessel behaviour while manoeuvring under external disturbances such as waves, currents and wind. The knowledge of the manoeuvring characteristics of a vessel allows time simulations of its path as a function of its control settings [11]. The new predictive tool based on ANNs has the objective to be an alternative to the usual manoeuvring simulators that use traditional mathematical models, which are function of the hydrodynamic forces and moment derivatives. These values are normally achieved from experiments performed with models in tanks. This procedure is time consuming and costly, requiring the use of a large specialized purpose built facility. Another disadvantage of this method is the intrinsic scale effect model-real ship.

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Recursive Neural Networks (RNNs) use the output of network units at time t as the input to other units at time $t + 1$, forming a recursive topology. Moreira & Guedes Soares [12] developed a dynamic prediction model of manoeuvrability using RNNs, which was applied to the data of the Mariner hull. The RNN model represents an implicit mathematical model for ships with known time

histories of manoeuvring motions. The inputs to the simulation are the orders of rudder angle and ship's speed and also the recursive outputs velocities of sway and yaw. In order to evaluate the accuracy of the RNN two types of manoeuvres were simulated for the Mariner hull: tactical circles and zigzags. The data generated to train the network in [12] were obtained from a manoeuvrability mathematical model performing the simulation of different manoeuvring tests. The RNN proved to be a robust and accurate tool for the manoeuvring simulations.

In [13] the same methodology is applied to analyse full-scale manoeuvring data from catamarans [14]. RNNs are trained with that data and afterwards model simulations are compared with the full-scale results. The training data were limited to turning manoeuvres. This paper is an extension of [13], but in addition to the circles zigzag manoeuvres were also considered. Results already obtained using this method to analyse full-scale manoeuvring data from fast patrol vessels [15] can be found in Moreira & Guedes Soares [3].

The next sections of the paper will be comprised by the following subjects: a brief description of the manoeuvring tests, an explanation of the neural network model and respective parameters, presentation of the results through the comparison between manoeuvring tests and simulations and, finally, the conclusions about the whole procedure.

2. DESCRIPTION OF THE MANOEUVRING TESTS

Manoeuvrability trials were conducted in the Transtejo's catamaran Alges, which properties are listed in Table 1. Due to operational constraints of the vessel schedule, the manoeuvrability trials finished up being carried out in windy conditions. The absolute wind speed varied from 15 and 35 knots (wind force between 4 and 7Bft) during the trials. These trials were carried out in water depths varying from 2.4 to 7.4m.

Table1 Main particulars of the catamaran tested

Waterline length	44.25m
Length overall	46.25m
Breadth overall	11.80m
Waterline breadth (single hull)	2.68m
Distance between centreplanes	9m
Depth	2.90m
Design draught	1.35m
Draught at trials (forward/aft)	0.92-1.01/1.17-1.25
Displacement (full)	176m^3
Block coefficient	0.548
LCB	-8.14%
Design speed	25kn
Service speed	20kn
Engines (each of 2)	966kW, 2100rpm
Propellers (each of 2)	waterjets LIPS
Steering devices	deflectable nozzles
Stopping devices	reversing buckets
Maximum nozzle deflection angle	32deg
Stopping devices	flow reversing buckets

The trial plan followed the IMO standards [16, 17]:

- Turning circles (at different rudder angles);
- Zigzag manoeuvres 20º-20º;
- Spiral manoeuvre;
- Stopping manoeuvre.

Turning circles were recorded at full approach speed and at an approach speed corresponding approximately to the engines' rpm of 50% of those at full speed.

As a result, 14 turning circles, 2 zigzags, 3 spirals and 3 stopping manoeuvres were recorded. Table 2 lists the kinematical parameters registered. The approximate uncertainty estimates were obtained from suppliers' data and from observing the noise level.

Table 2 Measured parameters

Parameter	Unit	Measuring tool	Range	Estimated uncertainty
Co-ordinates	m	DGPS	-	±5m
Absolute (ground) speed	m/s, kn	DGPS	0-28kn	±0.5kn
Absolute course angle	[º]	DGPS	0º - 360º	±1º
Heading angle	[º]	compass	0º - 360º, ±180º	±1º
Rudder deflection angle	[º]	gauge	±25º	±3º

The GPS unit generated instantaneous ship co-ordinates in terms of the latitude φ and longitude λ. These were transformed to the standard Cartesian earth co-ordinates of the ship's origin ξ_C and η_C with respect to the manoeuvre's starting point (Figure 1), which coincided with the location of the DGPS antenna (placed in the ship centre plane, near the midship plane):

$$\xi_C = \kappa\left(\phi - \phi_0\right) \quad (1)$$

$$\eta_C = \kappa\left(\lambda - \lambda_0\right)\cos\phi_0 \quad (2)$$

The subscript '0' denotes the initial values of the corresponding variables and κ is the conversion coefficient from minutes to meters equal to 1852m/min. After this initial transformation the co-ordinate ξ is supposed to be measured along the true meridian while η is along the parallel. However, when analysing the

trajectories, the co-ordinates were transformed further so that the origin of the earth axes matches the ship's position at the start of a manoeuvre and the ξ-axis is directed along the approach path.

The global time received from the GPS and the computer clock time were both recorded. The recording sampling time was equal to one second for both the GPS data and the ship's gauge that measured the rudder deflection angle, and 0.2-0.25s for the ship's compass that measured the heading angle.

The rotation rate r is determined by numerical differentiation:

$$r \approx \frac{\Delta\psi}{\Delta t} \tag{3}$$

where ψ is the heading angle. The time increment Δt is chosen as a compromise between the time resolution and the necessity to diminish the influence of rounding errors, which were up to 20% at the minimum time increment. The drift angle β was determined as:

$$\beta = \chi - \psi \tag{4}$$

where χ is the course angle provided by the GPS.

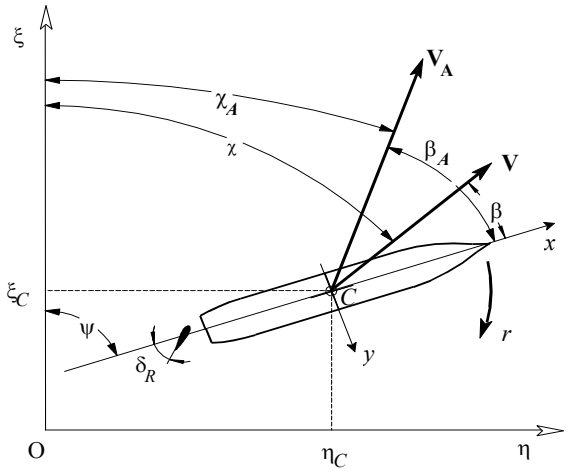

Figure 1 - Definition of kinematic parameters (all shown quantities are positive)

Observing the real trajectories shows that wind and current have some effect. They deform the trajectories and make it difficult to determine the manoeuvrability properties inherent to the ship. There is no simple correction method for wind except repeating manoeuvres. The situation is different for uniform current because its action is purely kinematic and this property remains approximately valid for typical slight non-uniformities. Thus, if the projections of the current velocity in the earth axes $V_{cur\xi}$ and $V_{cur\eta}$ are known, the corrected instantaneous coordinates of the ship ξ_{Ccor} and η_{Ccor} are given by:

$$\xi_{Ccor}(t) = \xi_C(t) - V_{cur\xi}t \tag{5}$$

$$\eta_{Ccor}(t) = \eta_C(t) - V_{cur\eta}t \tag{6}$$

The method for estimating the current velocity components designated in the appendix of the manoeuvrability standards, IMO [17], was adopted here. This method requires at least two points that belong to a trajectory of stationary circle with a difference of accumulated heading equal to 360º. In the absence of wind, the only reason for these two points not to coincide is a displacement caused by the current. The current velocity components can then be estimated through the inversion of Eqns.(5) and (6).

If one considers n pairs of points that satisfy the condition formulated above, the current velocity can be estimated using:

$$v_i = \frac{r_{360i} - r_i}{t_{360i} - t_i} \tag{7}$$

$$V_{cur} = \frac{1}{n}\sum_{i=1}^{n} v_i \tag{8}$$

where r_i is the vector position of the ship associated to its coordinates (ξ_C, η_C) at the instant t_i, and the subscript '360' refers to the positions of the ship corresponding after the heading has been changed by 360º. Generally, it is recommended to make the estimation of the current uniformity through the calculation of the square of the residual mean error of the current velocity value:

$$V_{cur}^{RMS} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(v_i - V_{cur}\right)^2} \tag{9}$$

It is recommended to consider the current as homogeneous if the error RMS does not exceed 20% of the estimated current velocity – this method of trajectory correction is not applicable in another way. Anyway, if the current velocity does not exceed 20% of the ship velocity during the manoeuvre the non-homogeneity of the current does not concern this study. This last condition was almost fulfilled during all the trials but the reason to omit the calculation of the error RMS was that the effect of the current was mixed with the effect of the wind. Thus it was impossible to estimate the current velocity not taking into account the wind influence. Therefore, the resulting estimation V_{cur} will not be considered as a current estimation, but as an equivalent constant velocity for the calculation of the total drift due to the current and wind.

The GPS software proved to be an excellent tool for acquiring the NMEA 0183 (National Marine Electronics Association Interface Standard) data in real time and for storing it in a suitable format for further processing. As both ship's heading and rudder angle appear with a high noise in their acquisition they had to be filtered applying a low pass filter. A Butterworth digital filter of fifth order (N=5) was used. The cut-off frequency ω_n was set to 1 Hz.

A more detailed description of the sea trials performed with the Alges catamaran is given in Guedes Soares et al [14], where the results are also shown.

3. NEURAL NETWORK TRAINING

The neural net that was used has 4 input nodes, 2 output nodes, and one hidden layer consisting of 10 nodes. Output parameters are the velocities of sway $v(t)$ and yaw $r(t)$. Input parameters are rudder angle $\delta(t)$, ship speed $V(t)$, and recursively the output parameters of the previous time step $v(t - 1)$ and $r(t - 1)$. For the first time step, when no output is available, initial conditions are used. A standard back propagation algorithm was used to train the network [18]. The binary sigmoid function is used in the case of the training of circles. It is a non-linear transfer function that operates on the inputs to the node and produces a smoothly varying output:

$$y(x) = \frac{1}{1 + e^{-x}} \tag{10}$$

A hyperbolic tangent *tanh* function is applied to each neuron in the hidden layer In the case of training the zigzag manoeuvres, providing a network with the ability to make soft decisions. The function is defined by

$$f(x, w) = \tanh\left[x^{lin}\right] = \frac{e^{2x^{lin}} - 1}{e^{2x_i^{lin}} + 1} \tag{11}$$

where $x^{lin} = \beta x$, with β being an additional parameter that controls the slope and is not adaptive; x are the inputs to the network and w are the weights between the input layer and the hidden layer.

Data for training, cross-validation and test the neural networks was acquired from full-scale trials performed with the Alges catamaran.

All nodes have a bias; this is implemented in the form of an extra weighted link to the node. The input to the bias link is the constant 1, which is multiplied by the weight associated with the link and then summed along with the other inputs to the node. The network contained a total of 16 computational nodes and a total of 72 weights and biases: 50 weights (4 inputs x 10 + 10 bias weights) related with the input data plus 22 (10 x 2 outputs + 2 bias weights) related with the output. The data was trained using proper software for this task and the obtained weights were used by the developed neural network into the overall simulation model.

4. COMPARISON BETWEEN MANOEUVRING TESTS AND SIMULATION RESULTS

Data collected from 22 manoeuvrability tests shown in Table 3, were used to train the RNN. Each circle test lasted in average about 7 minutes and each zigzag test lasted in average about 5 minutes. The sampling period used was 1 second and 8150 seconds of test data were available for the circles training. 2570 seconds of test data were available for the zigzags training. For the circles training the training data vector used 5704 (70%) of the total data. The remaining 2446 was used for cross validation and tests. For the circles training the training data vector used 1713 (70%) of the total data. The remaining 857 was used for cross validation and tests.

The ranges of variation of the parameter values were: $-32º < \delta < 32º$, $0kn < V < 26kn$, $-5.2m/s < v < 5.7m/s$, $-0.08rad/s < r < 0.09rad/s$. All these values were normalised between 0 and 1.

An attempt was made to use 20 nodes in the hidden layer. This did not change the accuracy significantly, while increasing computational times by 60%. This confirmed the conclusion from many applications that a minimum number of hidden units is needed for the network to learn the target function (desired) with enough accuracy, but extra hidden units do not significantly affect the generalisation ability.

If cross validation methods are not used to determine how many iterations must be executed, the increase in the number of hidden units usually increases the tendency of over-fitting the training data. Over-fitting results in excellent performance for the training data, but poorer generalisation ability for new data.

Table 3. Manoeuvrability full-scale trials

No.	Test	Approach Speed	Rudder Angle
1	Circle SB	8.5 kn	21º
2	Circle PS	8.8 kn	-32º
3	Circle PS	12.1 kn	-11º
4	Circle SB	12 kn	14º
5	Circle PS	12.5 kn	-21º
6	Circle SB	11.4 kn	32º
7	Circle SB	17.9 kn	11º
8	Circle SB	20.9 kn	19º
9	Circle PS	21.1 kn	-32º
10	Circle SB	21.2 kn	32º
11	Circle PS	25.6 kn	-10º
12	Circle SB	25.5 kn	16º
13	Circle PS	25.1 kn	-19º
14	Circle SB	25.3 kn	10º
15	ZigZag 20-20	20.6 kn	±20º
16	ZigZag 20-20	12 kn	±20º
17	ZigZag 10-10	10.1 kn	±10º
18	ZigZag 10-10	11.1 kn	±10º
19	ZigZag 10-10	15.3 kn	±10º
20	ZigZag 10-10	10.2 kn	±10º
21	ZigZag 20-20	19.2 kn	±20º
22	ZigZag 20-20	11.1 kn	±20º

A learning rate η = 0.1 and a momentum α = 0.7 were selected. Lower values produced equivalent generalisation ability for both parameters, but with longer training times. For considerably higher values, the training failed to converge to an acceptable error. The weights of all network units were randomly initialised and 65,500 iterations were used. A minimum error for the validation set after 65,500 iterations were obtained.

After 100 iterations the network performance was evaluated through the validation set. The final network selected was that with best accuracy through the validation set.

Figures 2-14 compare some of the results obtained by RNN simulation with full-scale trial results. The values of the estimated current in the turning circle manoeuvres are indicated below each figure.

The only information provided to the trained network was the time histories for the rudder deflection angle and for the advance speed of the ship and the initial conditions of the vehicle. The results for trial#3 are not presented due to the fact that the value of the estimated current velocity (1.42m/s) is higher than 20% of the catamaran speed (1.24m/s).

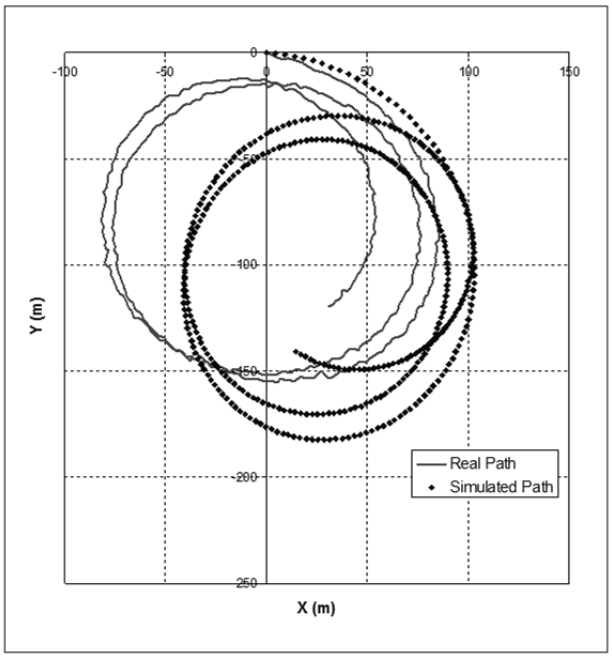

Figure 3 - Trial #2 – Circle PS
30% Full Speed – Full Rudder
V_{Cx} = -0.41 m/s; V_{Cy} = -0.3125 m/s;
Estimated V_{cur} = 0.5142 m/s
(Trajectories corrected for current effect)

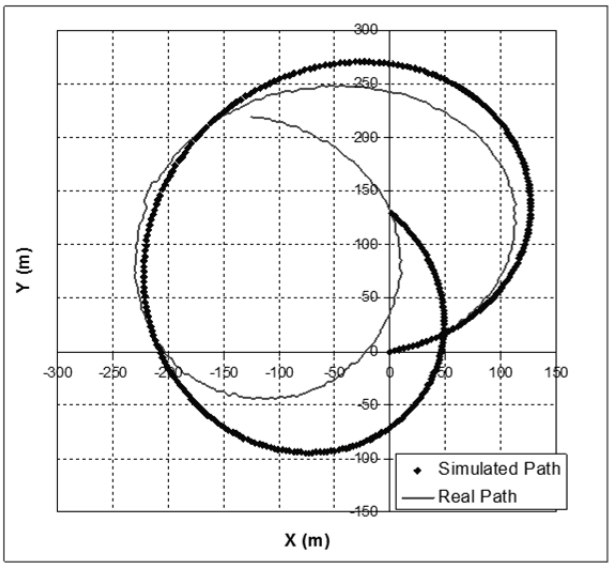

Figure 2 - Trial #1 – Circle SB
30% Full Speed – 65% Full Rudder
V_{Cx} = -0.25 m/s; V_{Cy} =-0.0101 m/s;
Estimated V_{cur} = 0.2519 m/s
(Trajectories not corrected for current effect)

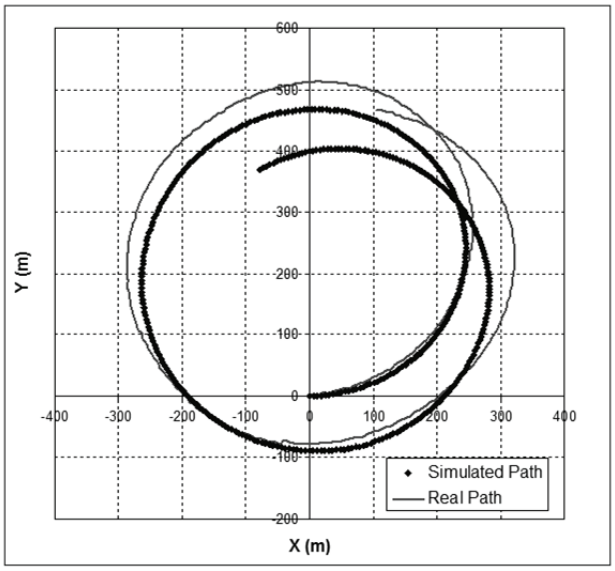

Figure 4 - Trial #4 – Circle SB
45% Full Speed – 45% Full Rudder
V_{Cx} = 0.24 m/s; V_{Cy} = -0.1085 m/s;
Estimated V_{cur} = 0.2606 m/s
(Trajectories not corrected for current effect)

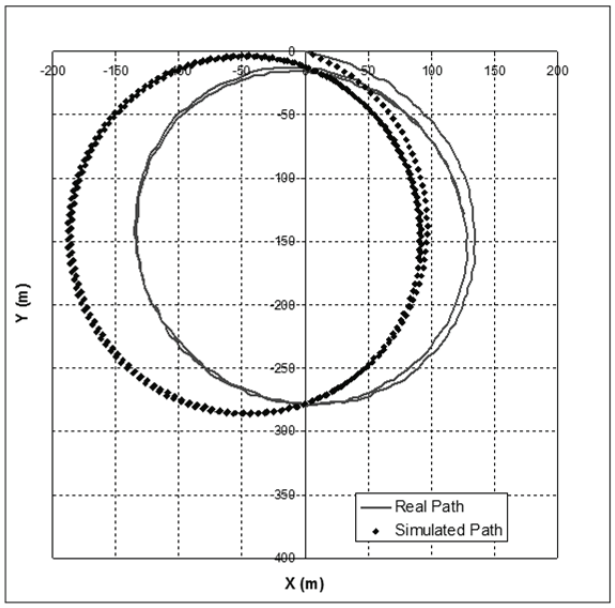

Figure 5 - Trial #5 – Circle PS
50% Full Speed – 65% Full Rudder
V_{Cx} = -0.49 m/s; V_{Cy} = -0.2047 m/s;
Estimated V_{cur} = 0.5313 m/s
(Trajectories corrected for current effect)

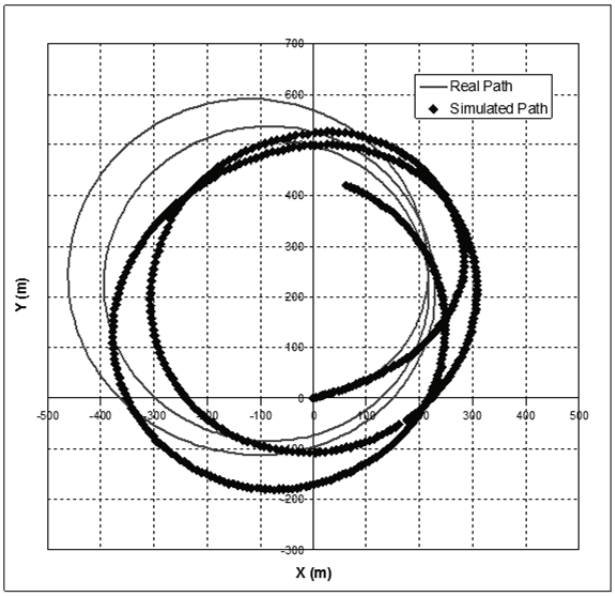

Figure 7 - Trial #7 – Circle SB
70% Full Speed – 35% Full Rudder
V_{Cx} = 0.48 m/s; V_{Cy} = 0.4746 m/s;
Estimated V_{cur} = 0.6779 m/s
(Trajectories corrected for current effect)

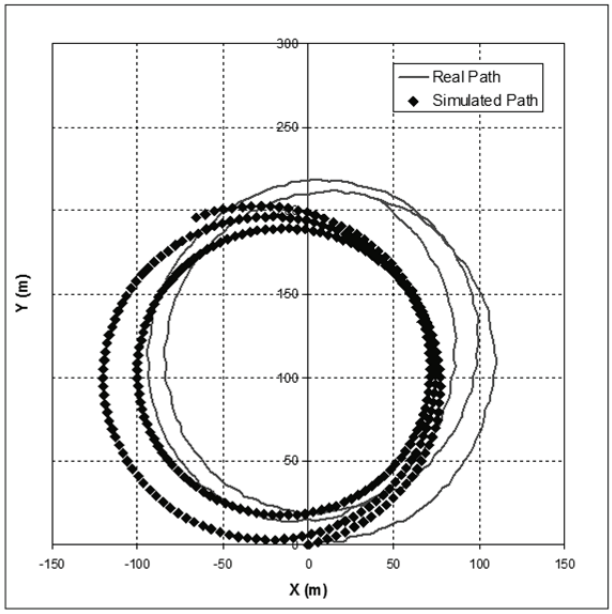

Figure 6 - Trial #6 – Circle SB
45% Full Speed – Full Rudder
V_{Cx} = 0.01 m/s; V_{Cy} = -0.2191 m/s;
Estimated V_{cur} = 0.2192 m/s
(Trajectories corrected for current effect)

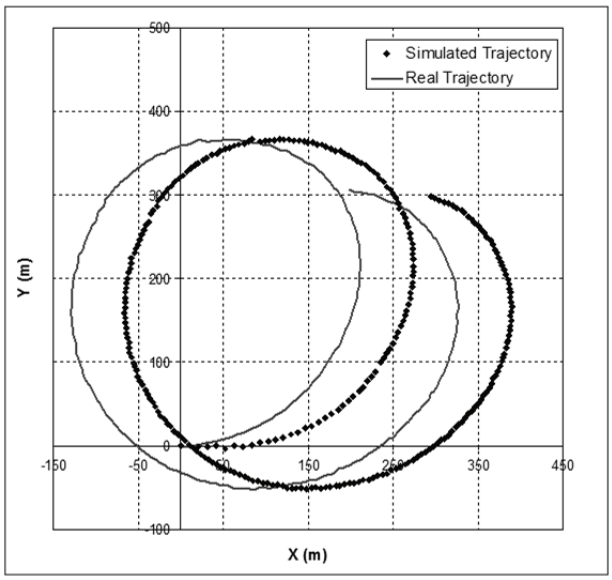

Figure 8 - Trial #8 – Circle SB
80% Full Speed – 60% Full Rudder
V_{Cx} = 0.69 m/s; V_{Cy} = -0.4963 m/s;
Estimated V_{cur} = 0.8464 m/s
(Trajectories not corrected for current effect)

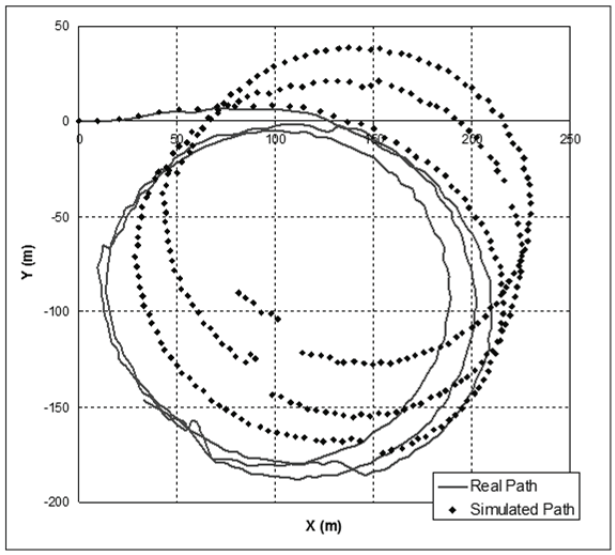

Figure 9 - Trial #9 – Circle SB
80% Full Speed – Full Rudder
V_{Cx} = 0.18 m/s; V_{Cy} = -0.3970 m/s;
Estimated V_{cur} = 0.4354 m/s
(Trajectories corrected for current effect)

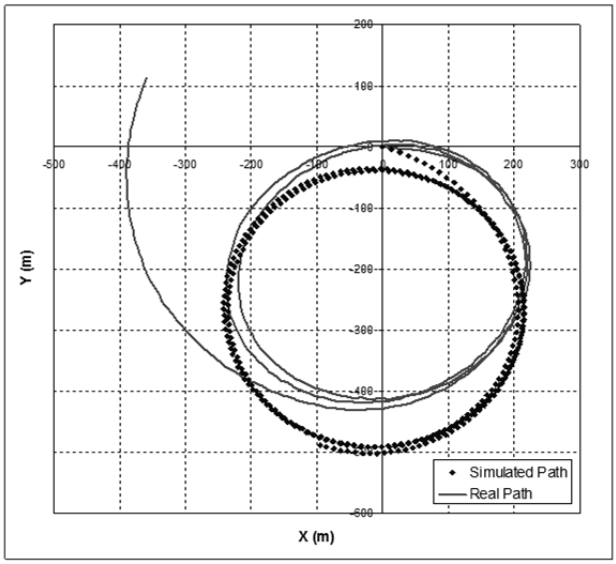

Figure 11 - Trial #11 – Circle PS
Full Speed – 30% Full Rudder
V_{Cx} = -0.45 m/s; V_{Cy} = -0.3331 m/s;
Estimated V_{cur} = 0.5590 m/s
(Trajectories corrected for current effect)

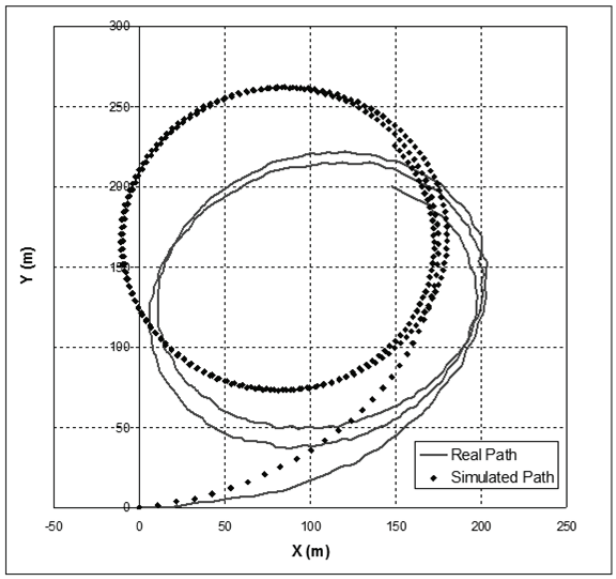

Figure 10 - Trial #10 – Circle SB
80% Full Speed – Full Rudder
V_{Cx} = 0.48 m/s; V_{Cy} = -0.2361 m/s;
Estimated V_{cur} = 0.5325 m/s
(Trajectories corrected for current effect)

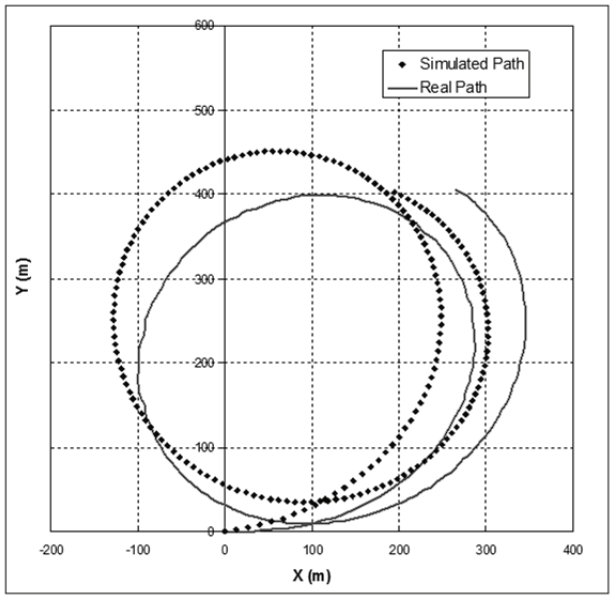

Figure 12 - Trial #12 – Circle SB
Full Speed – 50% Full Rudder
V_{Cx} = 0.54 m/s; V_{Cy} = -0.0850 m/s;
Estimated V_{cur} = 0.5511 m/s
(Trajectories not corrected for current effect)

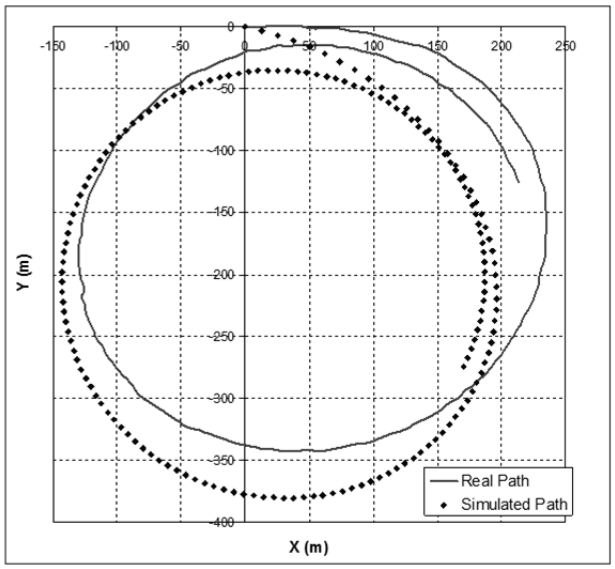

Figure 13 - Trial #13 – Circle PS
95% Full Speed – 60% Full Rudder
V_{Cx} = -0.36 m/s; V_{Cy} = -0.2350 m/s;
Estimated V_{cur} = 0.4264 m/s
(Trajectories corrected for current effect)

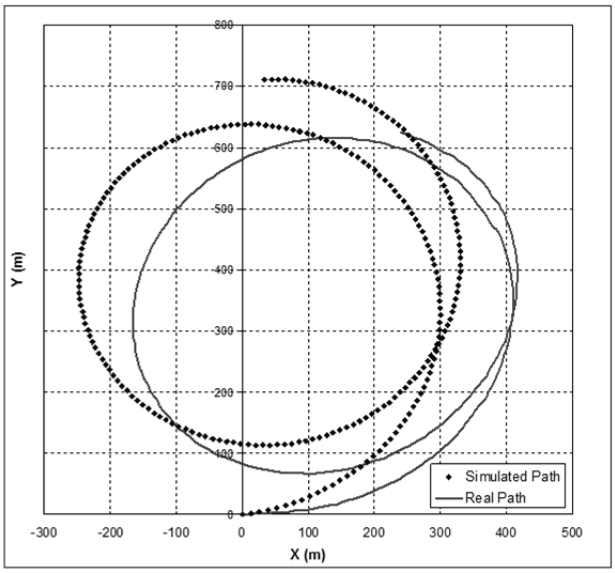

Figure 14 - Trial #14 – Circle SB
95% Full Speed – 30% Full Rudder
V_{Cx} = 0.17 m/s; V_{Cy} = 0.5140 m/s;
Estimated V_{cur} = 0.5399 m/s
(Trajectories not corrected for current effect)

In Table 1 are listed the absolute errors of x and y for each test as well as the values of the simulated diameter versus the real ones. The x and y errors are also given in percentage relative to the averaged value of the turning diameters.

Table 1 Tactical circles error measures

Test #		Simulated Diameter (m)	Real Diameter (m)	Error x	Error y	
1	x	339.43	341.56	2.12	17.71	m
	y	264.31	246.60	0.62	5.19	%
2	x	144.02	153.58	9.55	10.15	m
	y	210.58	200.44	6.22	6.61	%
4	x	507.54	541.84	34.30	44.59	m
	y	466.84	511.44	6.33	8.23	%
5	x	284.67	270.23	14.44	0.39	m
	y	279.45	279.84	5.34	0.14	%
6	x	197.52	204.15	6.62	16.35	m
	y	202.59	218.94	3.24	8.01	%
7	x	687.71	691.53	3.81	4.26	m
	y	706.73	702.47	0.55	0.62	%
8	x	308.68	338.85	30.17	2.67	m
	y	368.32	365.65	8.90	0.79	%
9	x	153.83	185.17	31.34	51.92	m
	y	255.62	203.71	16.93	28.04	%
10	x	160.30	164.63	4.32	16.51	m
	y	221.91	205.40	2.63	10.03	%
11	x	441.50	467.64	26.15	67.31	m
	y	506.49	439.18	5.59	14.39	%
12	x	369.72	377.47	7.75	51.22	m
	y	446.54	395.32	2.05	13.57	%
13	x	328.58	392.70	64.12	36.74	m
	y	395.75	359.02	16.33	9.35	%
14	x	544.30	569.25	24.96	22.66	m
	y	636.92	614.25	4.38	3.98	%
			Diameter Mean	Error x Mean	Error y Mean	
			364.79	19.97	26.34	m
				5.48	7.22	%

The predictions for the training circles are good in Figures 2-14. The averaged errors (over all the tactical circle manoeuvres) for x and y were 20 m and 26.3m, corresponding to relative errors (based on an average turning diameter of 364.8 m) of 5% and 7%, respectively.

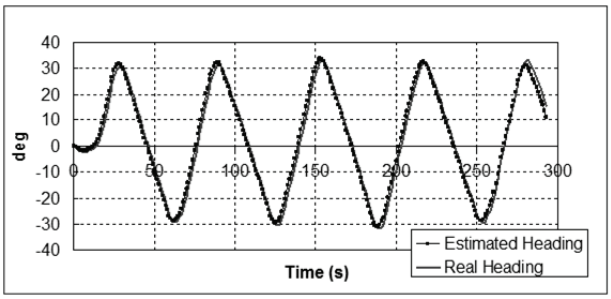

Figure 15 - Trial #15 – ZigZag 20-20 – 80% Full Speed

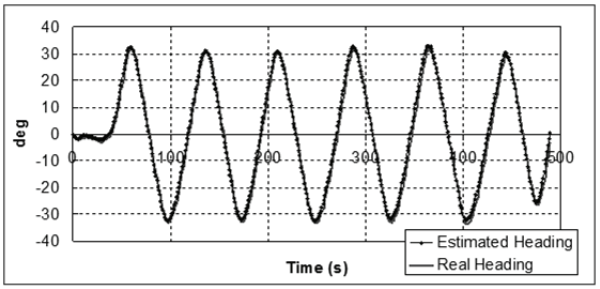

Figure 16 - Trial #16 – ZigZag 20-20 – 45% Full Speed

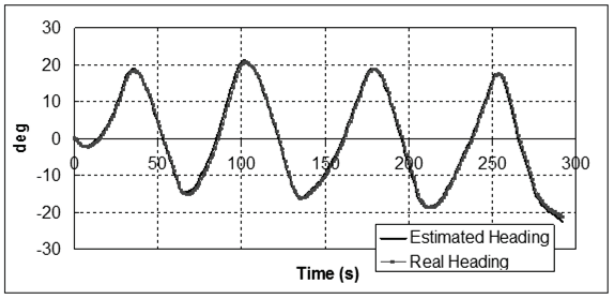

Figure 17 - Trial #17 – ZigZag 10-10 – 40% Full Speed

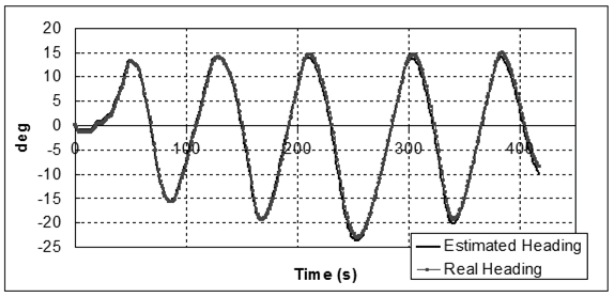

Figure 18 - Trial #18 – ZigZag 10-10 – 45% Full Speed

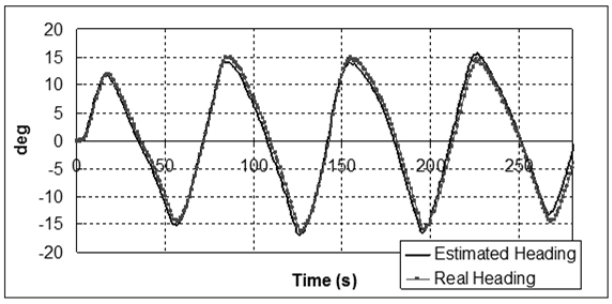

Figure 19 - Trial #19 – ZigZag 10-10 – 60% Full Speed

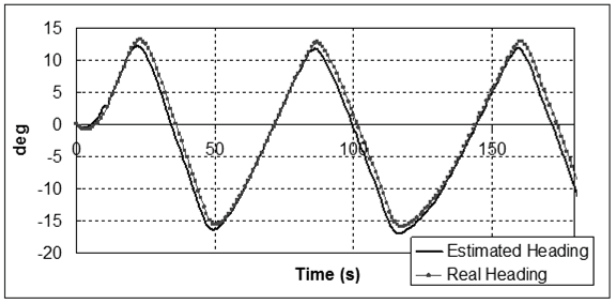

Figure 20 - Trial #20 – ZigZag 10-10 – 40% Full Speed

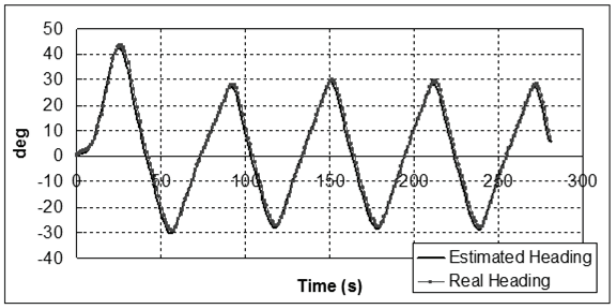

Figure 21 - Trial #21 – ZigZag 20-20 – 75% Full Speed

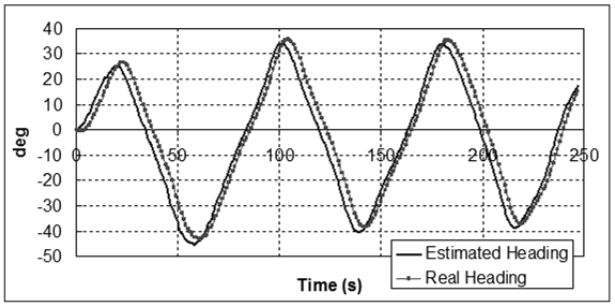

Figure 22 - Trial #22 – ZigZag 20-20 – 45% Full Speed

The results for the zigzags manoeuvres are shown in Table 2 for the variable ψ. In this table are given an error averaged over each one of the zigzag manoeuvres. The percentage errors were obtained by normalising with an average peak-to-peak heading variation of 27 deg.

Table 2 Zigzags error measures

Test #	Absolute Error ψ (deg)	Relative error ψ (%)
15	1.8	6.7
16	1.7	6.4
17	1	3.9
18	0.9	3.5
19	1.5	5.5
20	1.2	4.4
21	1.8	6.7
22	5.4	20.1
	Mean	Mean
	1.9	7.2

The predictions for the zigzag manoeuvres are also good, Figures 15-22. The absolute error for the heading angle averaged over all the zigzag manoeuvres was 1.9º corresponding to a relative error of 7%.

7. CONCLUSIONS

Recursive neural networks can be trained to predict manoeuvres based on sea trial data. The prediction quality depends on how important are the contaminating influences of environment and neglected input parameters. Despite limited training data and a simple model, the neural net learned how to predict manoeuvres satisfactorily. This application of ANNs to the manoeuvrability of ships can be extended, improved and validated with more data obtained from full-scale trials. One improvement to obtain better accuracy can be to insert more input parameters to the model and to introduce a greater number of tests for training.

8. ACKNOWLEDGEMENTS

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