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AN APPLICATION OF SOFT COMPUTING TECHNIQUES TO PREDICT DYNAMIC BEHAVIOUR OF MOORING SYSTEMS

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Summary

A spread mooring system (SMS) allows a ship or a floating platform to moor the seafloor using multiple mooring lines at a restricted region with a fixed heading in harsh weather. These systems can be used for the operations of ships of different tonnage at different sea depths. The optimal design of these systems is a challenging engineering problem because of the effects of many design parameters and changing environmental conditions. Modern soft computing techniques allow difficult engineering problems to be solved easily and precisely and are becoming more and more popular. In this paper, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) as soft computation techniques have been chosen to estimate the hawser tensions and displacements of a spread mooring system. The attained results show both techniques can give consistent indicators for the modelling of dynamic systems. Although these techniques performed very well, the ANFIS model is relatively superior to the ANN technique, considering the accuracy of hawser tensions and displacements in terms of the relative errors and coefficient of correlation obtained for the ANN and ANFIS.

Keywords: *Spread Mooring System; Soft Computing; Artificial Neural Network; Adaptive Neuro-Fuzzy Inference System; OrcaFlex*

1. Introduction

Because of engineering design studies, optimum solutions can be obtained, or a specific need can be met. These studies can be carried out from time to time under changing conditions and certain restrictions due to the nature of the work. Finding the optimal solution in a dynamic environment is one of the important goals of engineering studies.

Computer technologies are used effectively in the modelling of complex engineering systems. Conventional methods cannot solve complex, multi-objective decision problems, such as calculating the motion of a ship or an offshore structure. An effective technique for solving such problems is the genetic algorithm. Genetic algorithms offer much more effective and satisfactory results than conventional methods by solving multi-objective, non-linear, and discontinuous problems [1]. Genetic algorithms and artificial neural networks (ANNs) are techniques for optimization and learning, respectively, which both have been adopted from nature [2]. ANN can develop a model and solve problems quickly. Essentially, ANN is a computer modelling approach originated by the human brain to model non-linear multi-objective optimisation problems [3]. Adaptive Neuro-Fuzzy Inference System (ANFIS) is another soft computing technique defined by Jang for the modelling of complex problems [4]. ANFIS can develop a model using both fuzzy sets and artificial neural networks.

Artificial intelligence is commonly used in the marine industry. Guarize et al. employed an efficient method, including ANN and finite element [5]. They accomplished a non-linear mapping of system excitations to create the following system response for the examination of marine systems. Ozger and Sen developed an ANFIS model centred on the Takagi-Sugeno fuzzy modelling principles for approximating changes in wave features, such as zero up-crossing period and significant wave height because of wind speed [6]. Sylaios et al. estimated wave parameters using Takagi-Sugeno Fuzzy Inference System [7]. They used some characteristics of the environment in the modelling. Their model was applied to a data set recorded between 2000 and 2006 by a buoy set up in the Aegean Sea. This model forecasted the zero-up-crossing period and the significant wave height was better than conventional numerical models. Patil et al. employed an ANFIS that was trained on a set of data acquired from an experimental wave spread of a moored floating structure [8]. The correlation coefficient, error, and scatter in their study was effectively measured. Patil et al. presented an approach based on a Genetic Algorithm for estimating the wave spread of a moored floating structure [9]. They then compared the results with ANN and ANFIS on the statistic parameters. The performance of their model was found as superior. Pina et al. proposed an ANN proxy model, including a fast control tool, to examine and design marine systems [10]. They gained good outcomes, like the results of nonlinear dynamic analysis with a finite element. Pina et al. established a wavelet network architecture with a wavelet transform [11]. Their model is more efficient than ANN model. Queau et al. used OrcaFlex and FRONTIER to produce an extensive database of ANN training on marine systems [12]. They achieved to extend the range of input parameters and approximated over 99% of the cases of the databases with a ±5% error margin. Suhermi et al. used a hybrid model to take advantage of the ability of Autoregressive Integrated Moving Average (ARIMA) and ANN models in linear and nonlinear modelling compared to ARIMA and ANN model to roll motion prediction of a Floating Production Unit [13]. Wu et al. proposed a hybrid method for predicting multi-step-ahead wind and wave conditions, which combines a decomposition technique and ANFIS [14]. They showed that the forecast uncertainty increases with the prediction horizon, and a prediction range determined by the error factor provides a basic reference for the use of predicted environmental conditions for marine operations. Kim et al. proposed a data-driven prediction model based on the ANN to calculate the ice resistance of an ice-going vessel [15]. ANN was demonstrated to be able to efficiently model the nonlinear and complex systems without any prior assumptions and complex equations. Moreira and Soares presented an ANN model to estimate wave-induced ship hull bending moment and shear force from ship motions [16]. Yıldız used the ANN model to predict the residual resistance coefficient of a trimaran model [17]. A wide variety of ANN and ANFIS applications have also been carried out in the marine industry by several authors [18-25].

Spread-mooring systems allow tankers to be moored at fixed geographic locations under a range of weather conditions. These systems have a variety of applications with long service life and different vessel tonnages at different sea depths [26] There are two types of mooring systems: single or multiple points. Single-point systems continue to move in the environment to which they are attached until they reach the equilibrium position, while multi-point systems are fixed in an initial position.

The design of mooring systems is one of the important issues of the ship and offshore industry as it includes many parameters to be considered. The proper selection of the lines used, the number of line components, the line angle, the line length, the operation area, the sea condition, and the materials used make the design very complex. The correct selection of parameters has a significant impact on the system design. At this point, designers should consider the different combinations of system parameters. In addition, performing an optimization study including design parameters using innovative modelling techniques will help maximize the cost/benefit ratio and shorten the time spent in experimental or hydrodynamic simulation studies.

The aim of this study is to investigate the validity of soft computing techniques in marine industry engineering calculations. In this context, a real case is considered and ANN and ANFIS soft calculation techniques are used to estimate the mooring tensions and motion displacements of a moored ship. There is a significant loss of time and cost when experimental studies are preferred in the calculations of spread mooring systems. In addition, it is often impossible to provide sea conditions in a laboratory environment and some assumptions must be made. Also, it also takes a lot of time to calculate such systems with hydrodynamic analysis programs, such as OrcaFlex. In contrast, the proposed soft computing techniques provide significant savings in time and cost. Values to be obtained in 5-10 days in experimental studies or simulation studies can be easily calculated in one or two hours with ANN and ANFIS. And cost savings can be achieved with programs such as MATLAB that everyone can access for free.

2. Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems

ANN is a collection of artificial neurons. The human body contains approximately 10^{11} neurons, and the human brain comprises neurons [27]. Neurons work as a group and can be called a network. If the signals of the neurons do not have sufficient threshold values, the signals cannot be transmitted to other neurons. This movement of neurons affects their performance in processing systems.

There are many studies in the literature to develop ANN models. McCulloch and Pitts pioneered the first ANN study [28]. They developed a cell model using artificial nerve signals in their study. After this paper, some ANN studies have been materialized [29-32].

ANNs are used in many engineering problems, including forecast, classification, modelling, pattern recognition, and optimisation. ANN has many artificial neurons. The processing elements should be in the same direction in this structure. ANN structure has an input layer, a hidden layer, and an output layer (Figure 1).

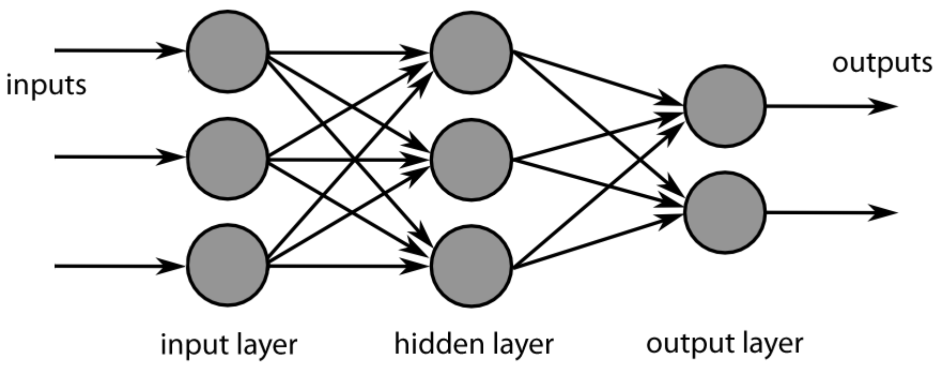

Fig. 1 ANN structure.

The input one takes inputs to send them to the hidden layer. The hidden layer processes the input data and transfers them to the output layer. The output layer provides the results of the system. ANN has five processing elements: inputs, weights, joining function, activation function, and outputs. The activation function makes ANN system nonlinear. The most common activation functions are tangent hyperbolic, linear and sigmoid activation functions (Figure 2).

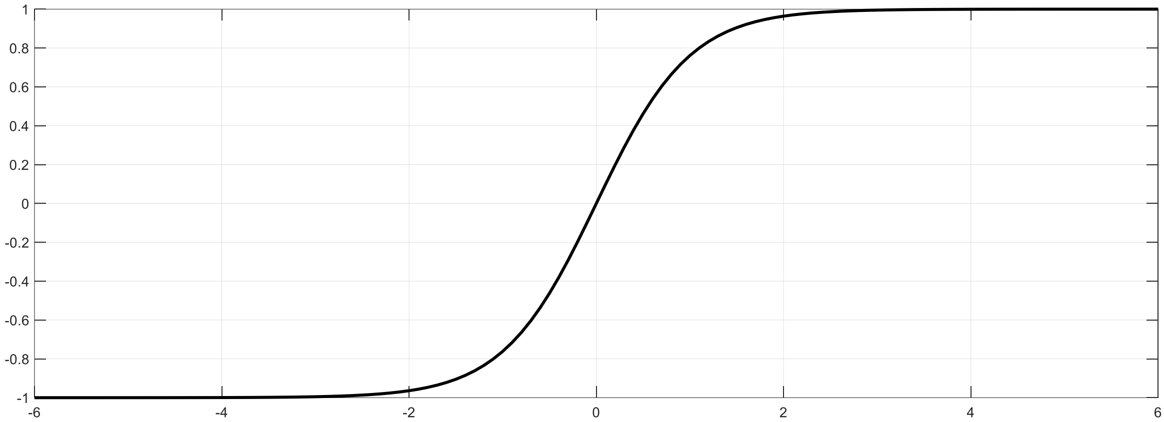

Fig. 2 Tangent hyperbolic activation function.

ANN has three methods for learning: unsupervised, semi-supervised, and supervised. Supervised learning is used the most. The real outputs and outputs of a model are compared. Also, ANN has several learning rules, such as Levenberg-Marquardt (LM), Kohonen, Hopfield, Delta, Hebb, and Back Propagation. The LM is an estimation of Newton's technique. In each iteration, the LM uses the parabolic approach as an approximation of the error surface and derives a solution to each step. The Hessian matrix in Eq. (1) is employed in the LM learning algorithm.

$$\boldsymbol{H = J^T J} \tag{1}$$

where J is the Jacobian matrix given in Eq. (2), is the initial derivative of the errors regarding the weights.

$$\boldsymbol{J(n) = \frac{\delta e(n)}{\delta w(n-1)}} \tag{2}$$

where n, δ, e, and w are the iteration number, differentiation symbol, error vector, and weight, respectively. Here, the gradient and weights are calculated by employing Eq. (3) and Eq. (4), respectively.

$$\boldsymbol{g = J^T e} \tag{3}$$

$$\boldsymbol{w_{k+1} = w_k [J^T J + \mu I]^{-1} J^T e} \tag{4}$$

where w_k, μ, and I are weight at k^{th} iteration, Marquardt Parameter (MP), and identity matrix, respectively. The MP is a scalar quantity. The LM algorithm will be the Newton algorithm when the MP becomes zero. The LM learning algorithm produces a result more rapidly than the other algorithms [33].

ANN technique has two network architectures: feed-forward and feed-back. Data is transmitted from the input to the output layers.

An adaptive neuro-fuzzy inference system (ANFIS) is a kind of artificial neural network that was developed in the early 1990s. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework.

Fuzzy sets were primarily presented by Zadeh [34], and many researchers have applied them to different engineering problems. In the fuzzy logic system, potential problems are divided into subsets. One technique is the Mamdani approach, which uses the experts' knowledge and provides the results as fuzzy numbers. As a fuzzy logic approach, Takagi and Sugeno employed if-then rules with a formula to solve complex problems [35]. ANFIS uses the Takagi-Sugeno type fuzzy model. This model excludes a defuzzification process. Instead of this process, it provides outputs as a formula of rules. Assume that ANFIS comprises two inputs (m_1, m_2) and one output (k). For the Takagi-Sugeno model, two fuzzy if-then rule sets are given the following statements.

Rule 1: If m_1 is X_1 and m_2 is Y_1; then $f_1 = x_1m_1 + y_1m_2 + z_1$

Rule 2: If m_1 is X_2 and m_2 is Y_2; then $f_2 = x_2m_1 + y_2m_2 + z_2$

where X_1, Y_1, X_2, and Y_2 are fuzzy sets, and x_i, y_i, and z_i (i=1,2) are the coefficients of the first-order linear polynomial linear functions. ANFIS has an input, a fuzzification, a rule, a normalization, and output layers (Figure 3).

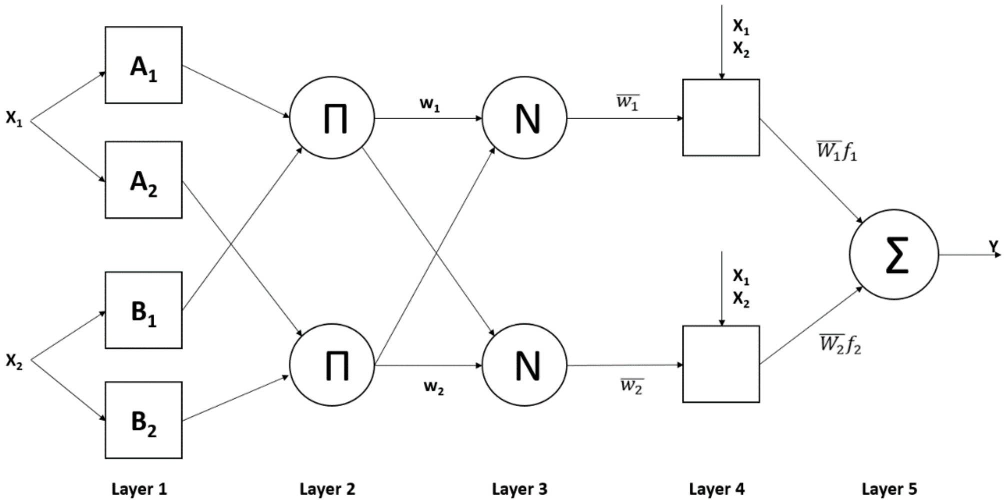

Fig. 3 General ANFIS structure.

In this study, there were 7 inputs for each output. Each input was divided into 3 fuzzy subsets, which are Gaussian combination membership functions (gauss2mf) shown in Eq. (5). The specific equation is given in Eq. (6).

$$\mathbf{y = gaussmf\ (x\ [sig1\ c1\ sig2\ c2])} \tag{5}$$

$$\boldsymbol{f(x;\sigma,c)} = \left\{ \boldsymbol{e}^{\frac{-(x-c)^2}{2\sigma^2}} \right\} \tag{6}$$

The gauss2mf function includes two (sig and c) parameters where sig1 and c1 identify the left side shape of the curve, and sig2 and c2 identify the right-side shape of the curve. When c1<c2, gauss2mf reaches its maximum value. The gauss combination membership function of the mooring angle is produced with 3 fuzzy subsets with the terms ‘Low’, ‘Moderate’, and ‘High’, as shown in Figure (4).

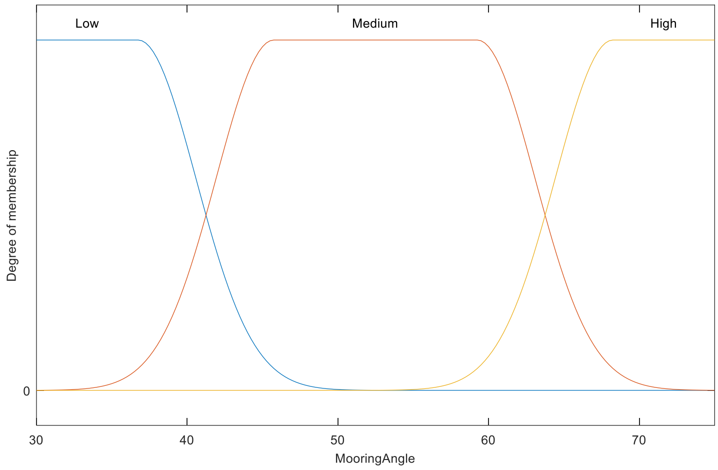

Fig. 4 Membership functions of the mooring angle.

The next step after the fuzzification is making rules with fuzzy sets. In this step, there are 7 inputs and all inputs are divided into 3 fuzzy subsets, so 37 rules are obtained for this study. These rules provide the output formulae for the system after normalization. Each of these steps is employed for every output individually because ANFIS can provide the results as a single output in a single case.

3. Modelling of Spread Mooring Systems

A tanker whose loading and unloading operations are carried out is highly affected by harsh weather conditions. To reduce or minimize the effects of environmental forces such as waves, currents, winds, tankers are tied to buoys with mooring lines. Sea depth, buoy types, bathymetry, and mooring line stiffness are significant parameters for the design of the system. The cost/benefit can be another important parameter. Materials, environmental conditions, and other options affect the cost directly. The prediction of hawser tensions and displacements is an important issue for the optimal design of the mooring systems. ANN and ANFIS can contribute to the SMS design process. Thus, time-consuming and expensive analysis methods can be avoided.

This article aims easily and precisely to predict the tensions and displacements of a moored ship using ANN and ANFIS. A station positioned on the Marmara Sea in Turkey was initially selected. The Sea of Marmara, also known as the Marmara Sea, is an inland sea located entirely within the borders of Turkey. That many tanker-buoy mooring systems were used in the region was effective in the selection of this station. Environmental conditions were described using the map of the Marmara Sea [36], and it was observed that the effective depth in the region where such systems were used was approximately 28 meters. The ABS classification procedures, regulations, and specifications were employed to get the properties of the SMS [37]. Regarding the environmental conditions of the region, which is an inland sea, the following extreme values were acquired:

- current velocity up to 2.5 knots,
- significant wave height up to 3 meters,
- wind speed up to 60 knots.

The OrcaFlex was used to model the spread mooring system in this study. The software simulates and performs dynamic calculations of marine structures, such as mooring lines, FPSO, SPAR, TLP, etc. The software uses a nonlinear time-domain finite element method in a 3D modelling environment [38]. In OrcaFlex simulation studies, the following parameters were taken considering the above-mentioned operational and extreme weather conditions.

- wave spectrum: JONSWAP,
- wave periods: 3.5-7.5 seconds,
- current calculation method: Power law,
- seabed type: flat,
- model: elastic.

The JONSWAP spectrum is defined as Eq. (7).

$$\boldsymbol{S(f)} = \left(\frac{\alpha g^2}{16\pi^4}\right)\omega^{-5} e^{\left(-\frac{5}{4}\left(\frac{\omega}{\omega_m}\right)^{-4}\right)} \gamma^{b} \tag{7}$$

where
g is the gravitational constant

$$b = e^{\left(-\frac{1}{2\sigma^2}\left(\frac{\omega}{\omega_m}-1\right)^2\right)} \tag{8}$$

$$\sigma = \begin{cases} \sigma_1 & for \quad \omega \leq \omega_m \\ \sigma_2 & for \quad \omega > \omega_m \end{cases} \tag{9}$$

$$\gamma = 6.0642, \alpha = 0.0217 \tag{10}$$

In addition, a set of experimental studies were carried out under different sea conditions to confirm some values obtained by OrcaFlex simulation studies. The experimental studies were carried out at the towing tank of the ITU Ata Nutku Ship Model Tank. The general characteristics of the tanker used in the experimental and simulation studies are given in Table 1.

Table 1 General characteristics of a tanker.

Characteristics	Units	Tanker
Displacement	Δ (tonnes)	125832
Length over all	LOA (m)	250
Length between perpendiculars	LBP (m)	228.2
Breadth	B (m)	38.71
Draft	T (m)	16.17
Longitudinal wind area	AL (m^2)	3601.4
Adverse wind area	AT (m^2)	857.2
Block coefficient	C_B	0.804

In the ship model tank, four ropes are moored as shown in Figure 5, two at the aft and two at the fore, for systems attached to the tanker at different degrees, such as 30, 45, 60, and 75. The lines were placed on the vessel in the range of 20% L (ship size) – 30% L. When the results obtained from the experimental studies were compared with the results obtained with the simulation program, it was seen that the values overlapped below the 5% margin of error. Therefore, it can be said that OrcaFlex data is consistent.

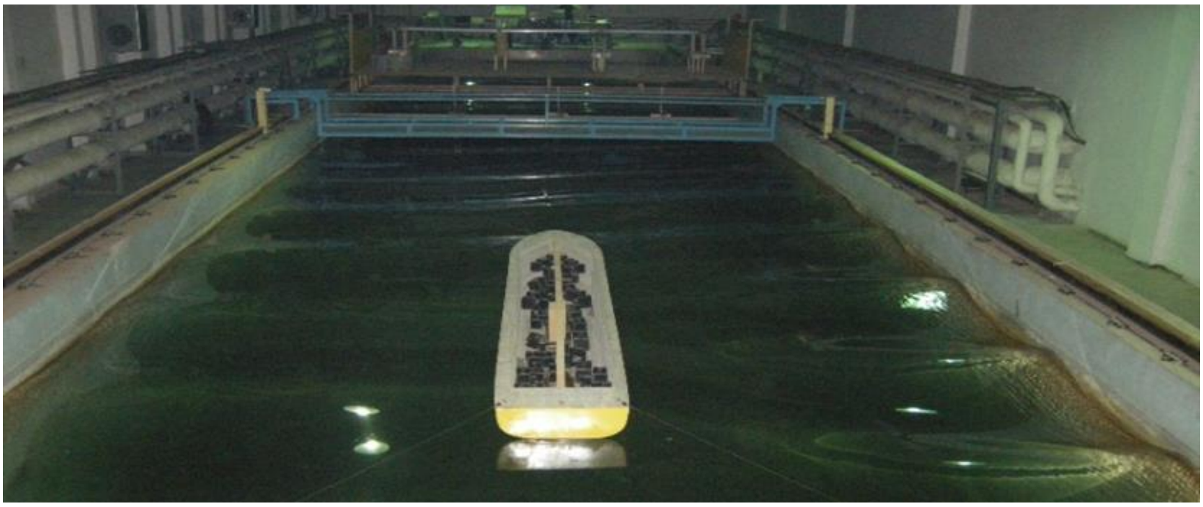

Fig. 5 Four-point tanker-buoy mooring system.

The OrcaFlex software was used to obtain the actual data required for ANN and ANFIS simulations. For this purpose, a set of simulation studies for an SMS were performed. Table 2 gives the environmental states used in the simulation studies. Table 3 shows the variables of simulations including the angle of environmental forces (e), significant wave height (h), wind speed (w), current speed (c), wave period (t), the angle of mooring lines (a) and the distance between the mooring point and the reference point (l).

Table 2 Range values of the used variables.

Direction	Wind Speed (m/s)	Current speed (m/s)	Significant Wave Height (m)	Wave Period (s)
South	0-30	0-2	0-5	3.5-7.5
Southwest	0-30	0-2	0-5	3.5-7.5
North	0-30	0-2	0-5	3.5-7.5
Northwest	0-30	0-2	0-5	3.5-7.5

The environmental conditions, the calculated tension, and displacement values were taken into account as input data for training. The data were separated randomly as given percentages for training, testing, and validation: 70%, 15%, and 15% of data for training, testing, and validation, respectively.

Table 3 Variables of the model.

e	h	w	c	t	a	l
10	3	2	1	4.5	45	40
30	3	5	2	5.5	60	35
30	2.5	13	1.5	5.5	60	50
45	4	8	1.5	5.5	45	70
150	2	1	2	4	60	0
170	3	3	2	5.5	45	50
180	3	1.5	3	6	75	30

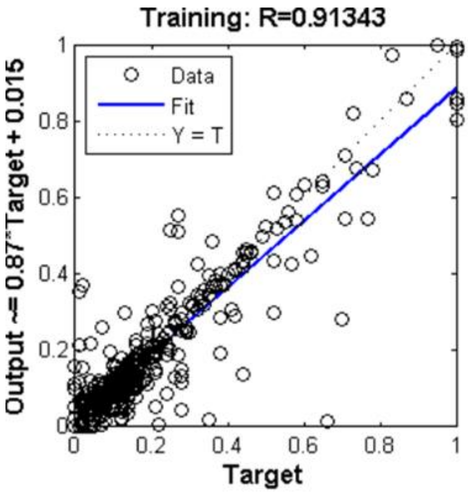

Fig. 6 Training results of ANN.

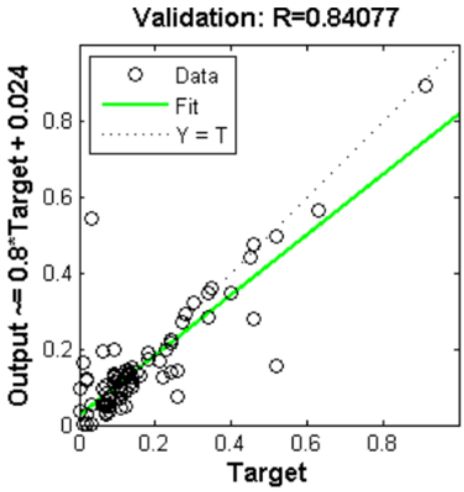

Fig. 7 Validation results of ANN.

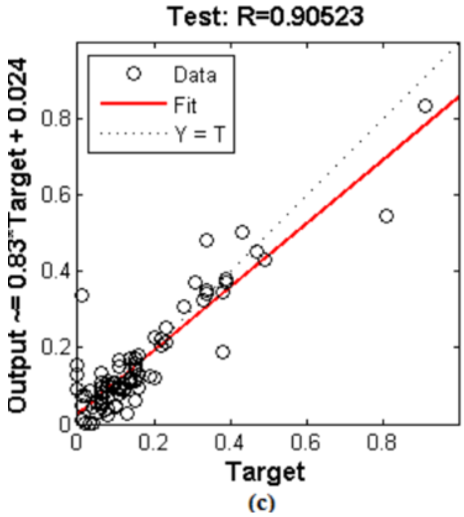

Fig. 8 Test results of ANN.

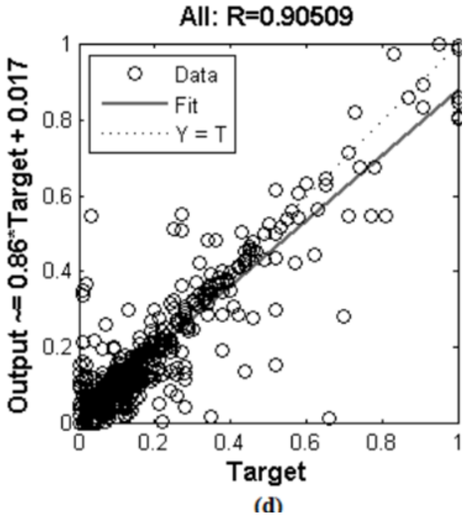

Fig. 9 Overall results of ANN.

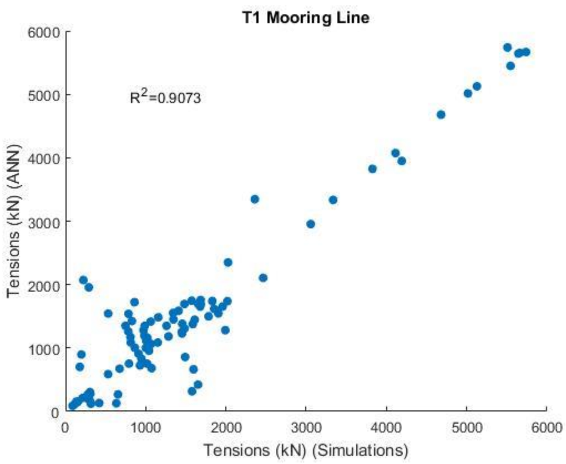

Fig. 10 ANN & simulation results for the T1 mooring line.

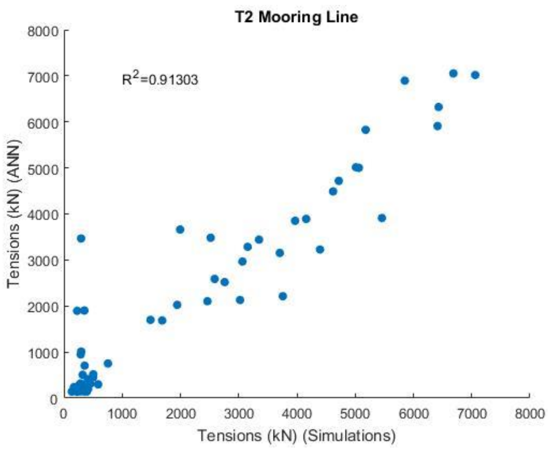

Fig. 11 ANN and simulation results for the T2 mooring line.

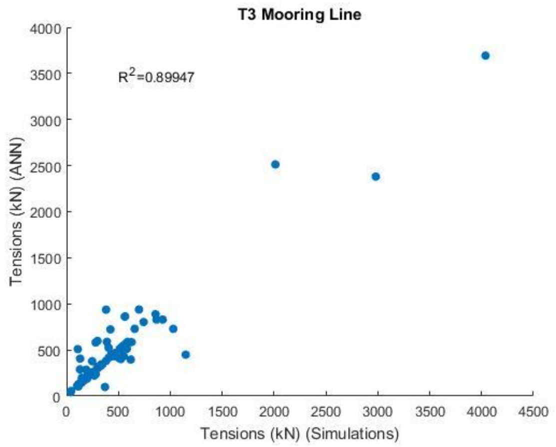

Fig. 12 ANN and simulation results for the T3 mooring line.

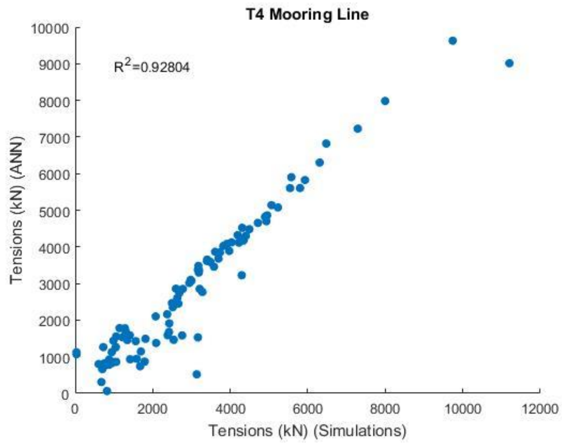

Fig. 13 ANN and simulation results for the T4 mooring line.

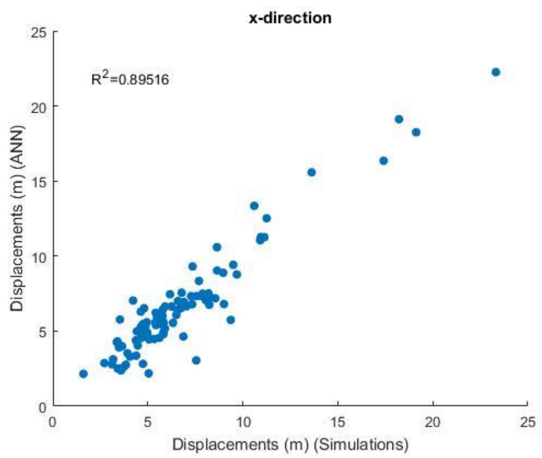

Fig. 14 ANN and simulation results for the displacement of a tanker at the x-direction.

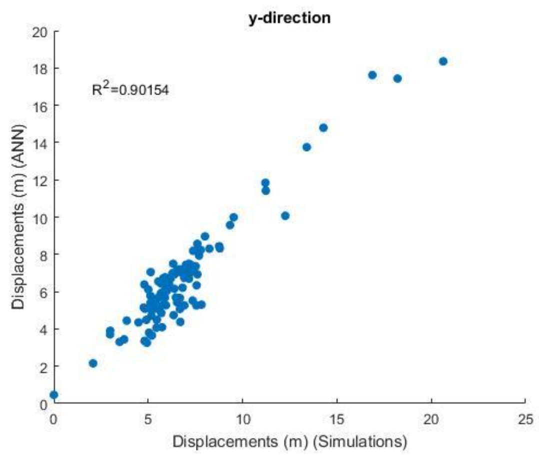

Fig. 15 ANN and simulation results for the displacement of the tanker at the y-direction.

The MatLab was used for ANN & ANFIS modelling. ANN architecture was taken as a feed-forward with 14 neurons in the hidden layer. Tangent hyperbolic activation function and LM as a learning algorithm were used. The learning rate of ANN model was 0.01 and the number of epochs was 1000. ANN training resulted in a 91% success rate (Figures 6-9). Figures 6-9 also illustrate the test and validation results of ANN. All was performed well with an accuracy of 90.5%. Besides these outcomes, Figures 10-15 compare the ANN and simulation results. The comparison of mooring line tensions and displacements of the tanker at the x and y-directions highlights the success of ANN to predict the tensions and displacements of tanker-buoy mooring systems.

As another technique, ANFIS was employed in SMS modelling. ANFIS model consists of four stages. These stages are data entry, assigning fuzzy sets, using the training function to learn the input data, and output estimation, respectively.

The accuracy of ANFIS model was 99.95%, which is higher than that of ANN model. Figures 16-21 compare the results of mooring lines' tensions and motion displacements. Figures 22-33 present the results obtained from ANN and ANFIS models. It displays ANFIS prediction values are almost close to the simulation/experimental values compared to ANN values. ANFIS prediction delivers the best fit to the experimental/simulation results and yields a better prediction of the hawser tensions and displacements of the SPM.

When we analyze ANN and ANFIS results for mooring line 1 (T1) in Fig. 10 and Fig. 16, it is clear that ANFIS performed better than ANN. The results of mooring line 2 (T2) in Fig. 11 and Fig. 17 show that even though ANN has 90.5% of success in terms of R^2, ANFIS presents better results with 99.95% of success. Similar results can be observed for mooring line 3 (T3) and mooring line 4 (T4) in Figures 12, 18 and Figures 13, 19, respectively. In terms of displacement along x and y axes in Figures 14-15 and Figures 20-21, the results of ANN for R^2 get lower compared with those in the mooring line tension results whereas the results of ANFIS get better. Figures 22-33 show collective results of ANN and ANFIS for tensions and displacements with line graphs. Summary of results is also listed in Table 4 for simulations, ANN and ANFIS results. Error Analysis and correlation coefficients were calculated for ANN and ANFIS and are given in Table 5. As seen in Table 5, the correlation coefficients reached by the correlation analysis of the data obtained with ANN and ANFIS are over 0.8, which indicates a very high correlation.

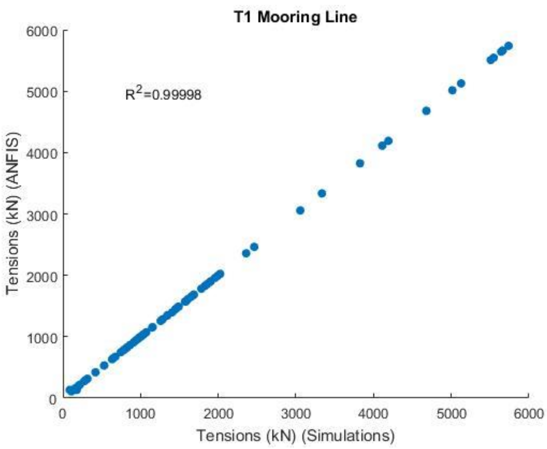

Fig. 16 ANFIS and Simulation results for the T1 mooring line.

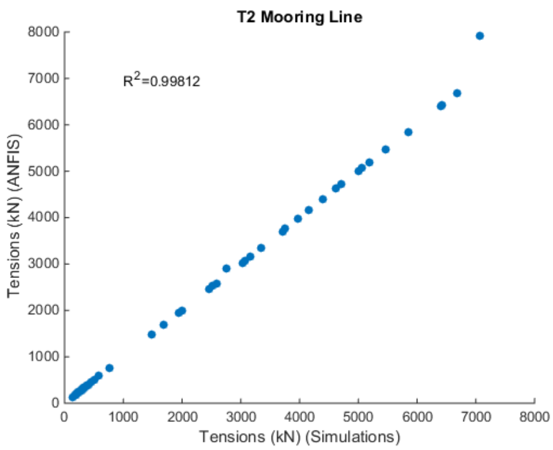

Fig. 17 ANFIS and simulation results for the T2 mooring line.

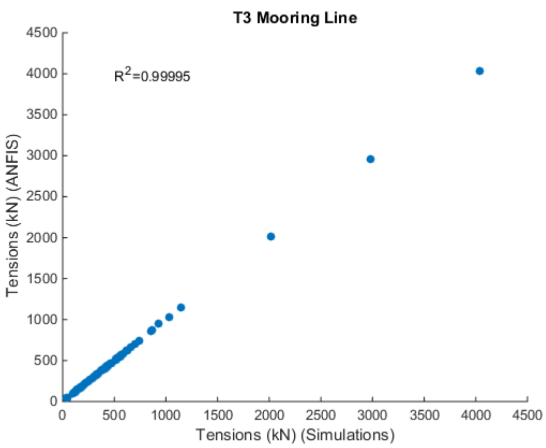

Fig. 18 ANFIS and simulation results for the T3 mooring line.

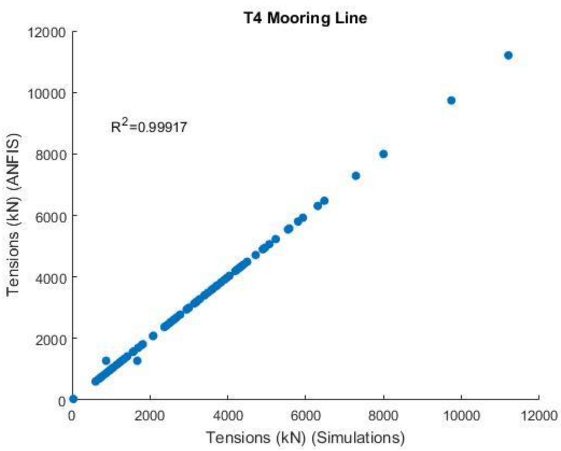

Fig. 19 ANFIS and simulation results for the T4 mooring line.

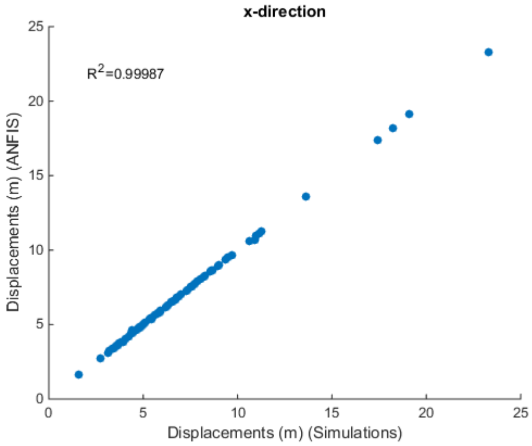

Fig. 20 ANFIS and simulation results for the displacement of a tanker at the x-direction.

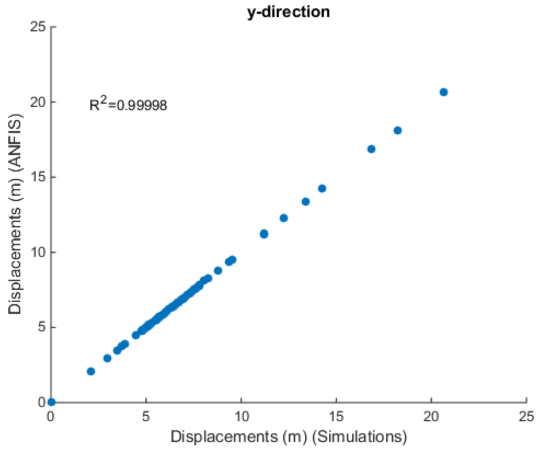

Fig. 21 ANFIS and simulation results for the displacement of a tanker at the y-direction.

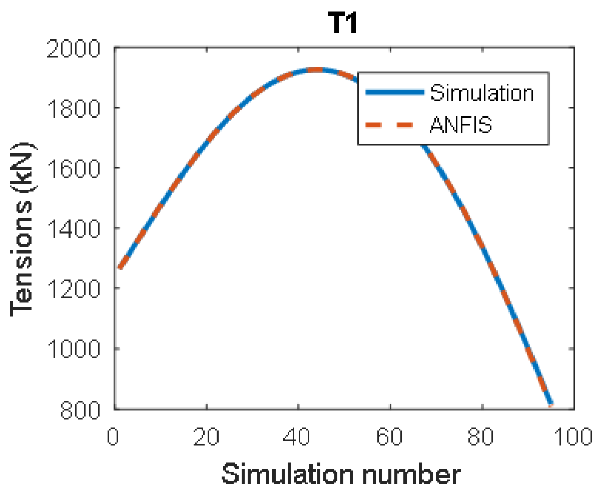

Fig. 22 Comparison of simulation and ANFIS model for T1.

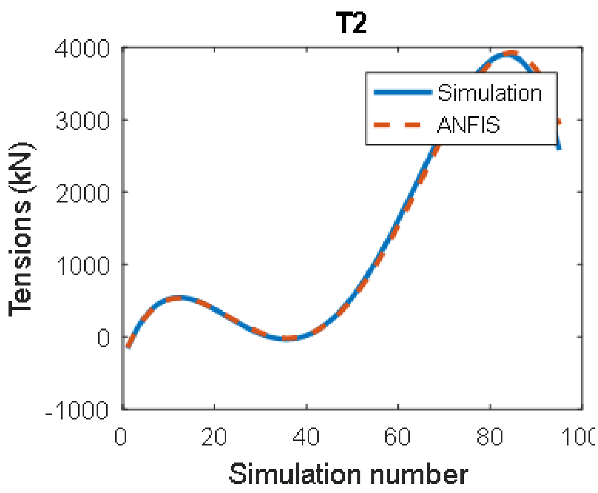

Fig. 23 Comparison of simulation and ANFIS model for T2.

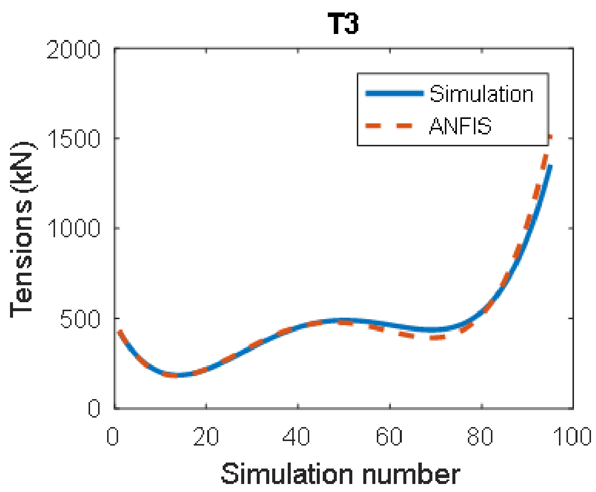

Fig. 24 Comparison of simulation and ANFIS model for T3.

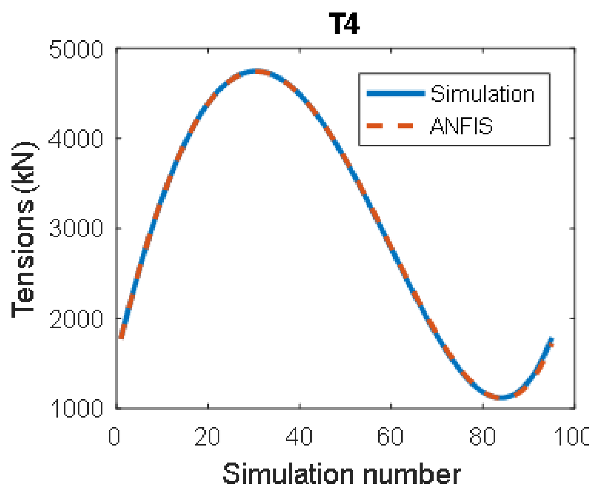

Fig. 25 Comparison of simulation and ANFIS model for T4.

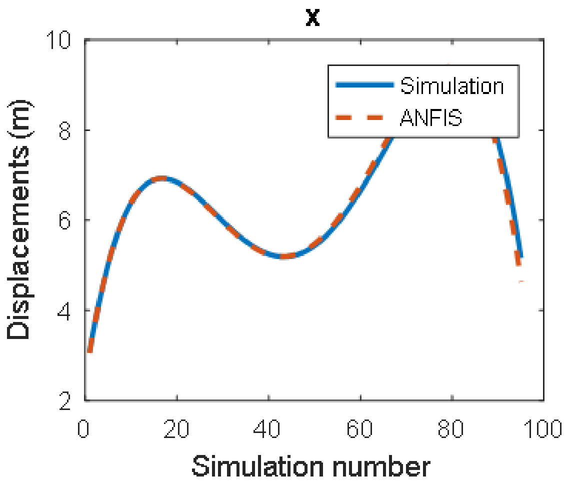

Fig. 26 Comparison of simulation and ANFIS model for the displacement of the tanker at the x-direction.

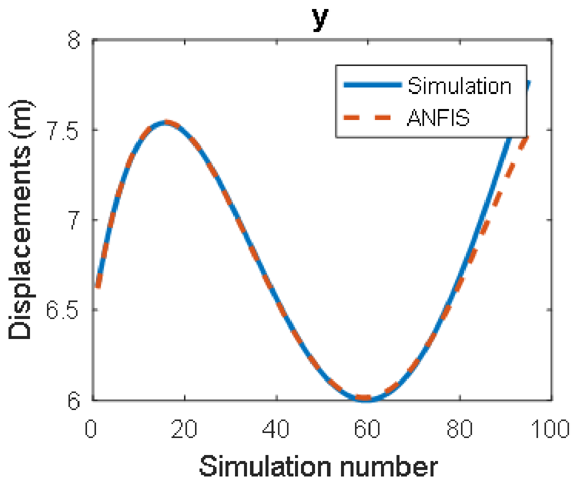

Fig. 27 Comparison of simulation and ANFIS model for the displacement of the tanker at the y-direction.

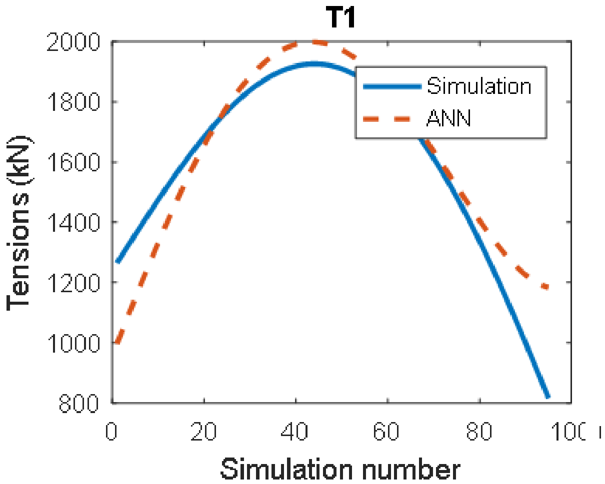

Fig. 28 Comparison of simulation and ANN model for T1.

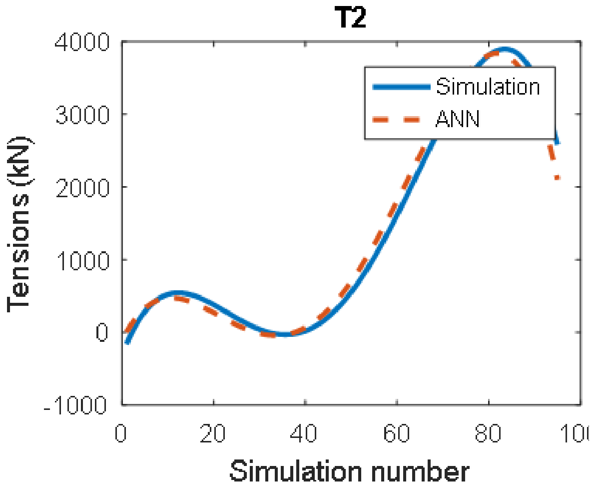

Fig. 29 Comparison of simulation and ANN model for T2.

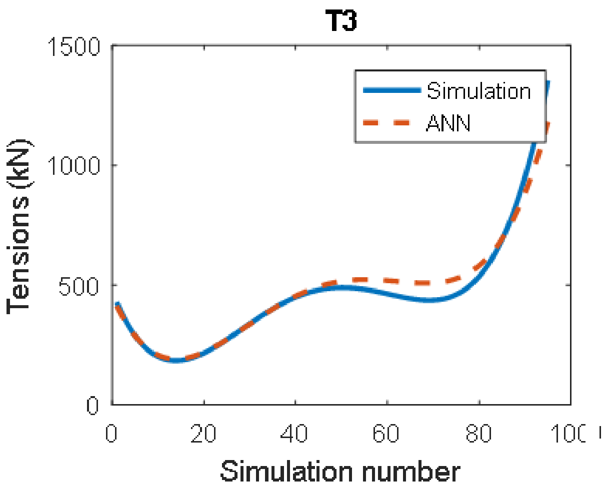

Fig. 30 Comparison of simulation and ANN model for T3.

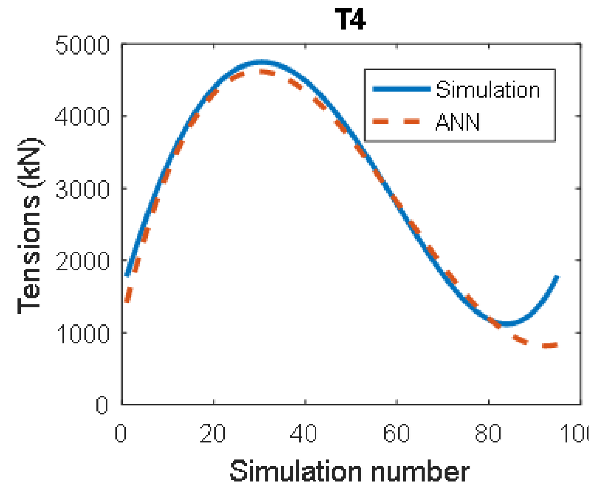

Fig. 31 Comparison of simulation and ANN model for T4.

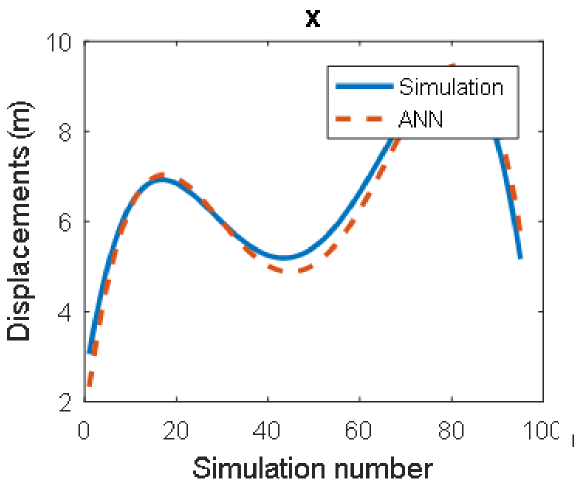

Fig. 32 Comparison of simulation and ANN model for the displacement of the tanker at the x-direction.

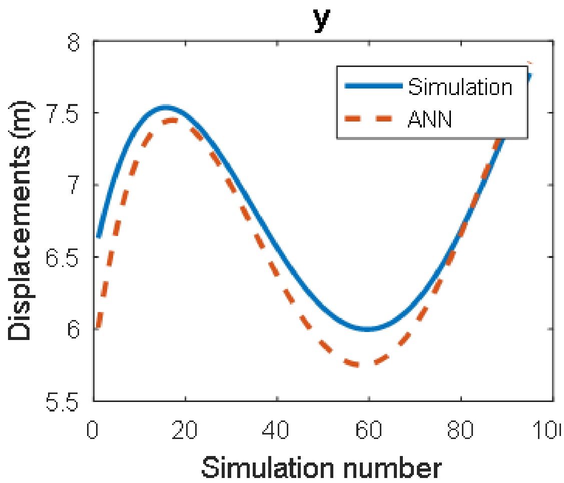

Fig. 33 Comparison of simulation and ANN model for the displacement of the tanker at the y-direction.

Table 4 Summary of simulations, ANN and ANFIS results.

Simulation	T1	674.5	791.0	1149.8	1684.7	1829.5	1585.0	1610.2	1905.1
	T2	3968.6	308.5	191.9	256.3	247.5	233.1	231.5	247.2
	T3	4038.5	163.8	333.6	115.4	113.8	436.5	439.9	431.5
	T4	871.6	1299.4	2660.9	3821.8	4037.5	3973.5	4220.1	4492.7
	x	7.6	2.7	3.4	4.9	4.9	6.6	7.3	8.2
	y	14.3	5.1	5.6	5.7	5.7	7.3	7.3	7.0
ANN	T1	674.5	754.9	1086.7	1757.8	1740.3	1376.9	1446.5	1546.0
	T2	3850.0	182.7	148.0	247.8	266.1	212.5	136.0	218.4
	T3	3693.2	173.8	343.6	105.4	103.8	436.5	439.9	431.5
	T4	830.5	1695.5	2450.2	4025.3	4125.4	3889.9	4116.5	4483.0
	x	7.3	2.9	4.3	5.3	5.0	7.0	7.3	7.5
	y	14.8	3.7	5.7	6.4	5.9	7.2	7.4	7.4
ANFIS	T1	674.5	791.0	1149.9	1684.8	1829.6	1575.6	1614.9	1905.1
	T2	3968.6	308.5	191.9	255.7	247.9	232.8	231.7	247.6
	T3	4038.5	163.8	333.6	115.6	113.8	435.7	440.8	432.2
	T4	871.6	1299.4	2660.9	3821.7	4037.5	3973.1	4221.1	4493.0
	x	7.6	2.7	3.4	4.9	4.9	6.6	7.3	8.2
	y	14.3	5.1	5.6	5.7	5.7	7.3	7.3	7.0

Table 5 Correlation and Error Analysis.

	ANN						ANFIS					
	T1	T2	T3	T4	x	y	T1	T2	T3	T4	x	y
Absolute Error	0.0%	3.0%	8.6%	4.7%	3.9%	3.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	4.6%	40.8%	6.1%	30.5%	7.4%	27.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	5.5%	22.9%	3.0%	7.9%	26.5%	1.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	4.3%	3.3%	8.7%	5.3%	8.2%	12.3%	0.0%	0.2%	0.2%	0.0%	0.0%	0.0%
	4.9%	7.5%	8.8%	2.2%	2.0%	3.5%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
	13.1%	8.8%	0.0%	2.1%	6.1%	1.4%	0.6%	0.1%	0.2%	0.0%	0.0%	0.0%
	10.2%	41.3%	0.0%	2.5%	0.0%	1.4%	0.3%	0.1%	0.2%	0.0%	0.0%	0.0%
	18.8%	11.7%	0.0%	0.2%	8.5%	5.7%	0.0%	0.2%	0.2%	0.0%	0.0%	0.0%
Correlation	0.96	1.00	1.00	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00

4. Conclusions

The prediction of the hawser tensions and displacements is important for the optimal design of the SMS. ANN and ANFIS can be effectively used to predict the behaviour of such systems. These soft computing techniques are powerful tools for obtaining the correlation between the input and output in complex systems.

In this study, to estimate hawser tensions and displacement of a moored tanker first of all, a four-point mooring system was modelled, and this system was simulated using OrcaFlex to get required data for ANN and ANFIS. Afterwards, some experiments were conducted on the Ata Nutku Ship Model Testing Laboratory to test the accuracy of the simulation studies and verify the consistency. In the continuation of the study, the OrcaFlex simulation results were used to train the ANN and ANFIS models. Then, the simulation outputs were employed to train ANN and ANFIS models. Finally, ANN and ANFIS outputs were analysed and error and consistency analyses were carried out.

In the ANN, the data with R-values of 0.91343, 0.84077, and 0.90523 were recorded for the training, validation, and testing respectively, while the overall R-value of 0.90509 was obtained for the overall training process. Correlation coefficient values in the ANN were got in the range of 0.96-1.00 and showed a high correlation, but the same success could not be seen in absolute error calculations (see Table 5). In the calculations made with the ANFIS model, a very high accuracy of 99.95% was achieved. In the calculations made with the ANFIS model, a very high accuracy of 99.95% was achieved. Precise correlation and near-zero absolute error estimates are obtained for all hawser tensions and displacements in ANFIS.

In other words, more precise results were acquired in ANFIS model compared to ANN model. The outcomes showed both models are reliable in estimating the SMS characteristics, but ANFIS model without mathematical modelling provides a better solution for the problem of the non-linear prediction of the SMS.

In further studies, these techniques can be applied to the modelling of marine structures with different mooring lines. Also, different prediction methods can be employed, or combined with the current methods to get cost-effective designs.

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