Proceedings of the ASME 2017 36th International Conference on Ocean, Offshore and Arctic Engineering
OMAE2017
June 25-30, 2017, Trondheim, Norway

OMAE2017-61474

SIMPLIFYING NEURAL NETWORK BASED MODEL FOR SHIP MOTION PREDICTION: A COMPARATIVE STUDY OF SENSITIVITY ANALYSIS

Xu Cheng, Shengyong Chen, Chen Diao, Mengna Liu
School of Computer Communication and Engineering
Tianjin University of Technology
Tianjin, 300384 PR China

Guoyuan Li*, **Houxiang Zhang**
Department of Ocean Operations and Civil Engineering
Norwegian University of Science and Technology
Aalesund, 6009 Norway

ABSTRACT

This paper presents a comparative study of sensitivity analysis (SA) and simplification on artificial neural network (ANN) based model used for ship motion prediction. Considering traditional structural complexity of ANN usually results in slow convergence, SA, as an efficient tool for correlation analysis, can help to reconstruct the ANN model for ship motion prediction. An ANN-Garson method and an ANN-EFAST method are proposed, both of which utilize the ANN for modeling but select the input parameters in a local and a global fashion, respectively. Through the benchmark tests, ANN-EFAST exhibits superior performance in both linear and nonlinear systems. Further test on ANN-EFAST via a case study of ship heading prediction shows its cost-effective and timely in compacting the ANN based prediction model.

INTRODUCTION

With the development and prosperity of the world's shipping industry, the maritime transportation has become more and more busy. In order to ensure the safety of navigation, great concern has been put toward the ship motion prediction. Furthermore, some special operations, such as submarine cable laying, marine survey, etc., need more accurate ship motion prediction and control precisely. Therefore, how to establish an efficient ship motion prediction model has great theoretical and practical value in the maritime applications. However, mathematical model based ship motion prediction is challenging due to the nonlinear and time-varying dynamical model of ship, as well as complex dynamic nature of sea [1, 2]. Our partner in Norway therefore started to collect on-board ship sensor data long time ago and intended to create robust predictive models for ship maneuvering technologies. There would be a possibility to combine those ship sensor data with modeling methods to design and implement ship motion prediction model.

To date, a variety of novel intelligent approximation-based techniques and algorithms like fuzzy logic, Kalman filtering, Bayesian network, regression analysis and ANN have been applied to create predictive models [3–6]. Those methods have their own pros and cons at specific aspects. For example, regression analysis is not suitable for complex, high dimensional and non-linear system; Fuzzy logic relies more on mathematical model; Kalman filtering works only for Gaussian noise process; The performance of Bayesian network in high dimensional data set is poor. None of them except ANN are suitable for modeling the ship motion, as situations in which lack precise mathematical model and only input-output sample data are available.

Indeed, an ANN is a "black box" and has the ability to explicitly identify possible causal relationships from the input-output sample data. However, there is no standard to construct a compact ANN for prediction purposes. Input parameters and hidden units are the main factors to obtain an optimized model [7]. If there are too few inputs, the network cannot represent the input-output mapping of system with sufficient accuracy. If there are too many inputs, the network dimension will increase, which in turn aggravates computational complexity. Both cases will deteriorate the generalization capability of the network. Therefore, selection of input parameters is a key issue when applying ANN

*Corresponding author, Email: guoyuan.li@ntnu.no. Xu Cheng and Guoyuan Li have equal contribution to this paper.

to ship motion prediction. SA investigates how the variation in the output of a numerical model can be attributed to variations of its input factors, and it plays an important role in prediction model construction and simplification, and thus the generalization ability of prediction model. The main purpose of SA is to estimate the contribution of each model input, either main or interaction contribution, on the model output and to identify the main contributors to the output. SA has been widely used in areas such as engineering, economics, and sociology [8]. Taking advantages of SA's characteristics, it is possible to use it to select the input parameters of an ANN based model used for ship motion prediction.

The rest of the paper is organized as follows. The related work section is a brief recall of some of the existing methods in ANN and SA. In the next section, we describe the input selection procedure and the case ship, then the methods we used in this paper is introduced and the calculation of local sensitivity analysis (LSA) and global sensitivity analysis (GSA) are explained. After that, the proposed algorithm is tested using two analytical models and a case study of SA on heading of ship motion prediction model is described in detail. The results are shown and the calculated first order sensitivity index are compared with analytical results. A comparison of the performance of the LSA and GSA is also presented in this section. Finally conclusions are given.

RELATED WORK

Artificial Neural Network

Inspired by biological neural network, ANN could build up the mathematical relationship between the input parameters and the output parameters, with the advantage that it can be modeled without prior knowledge. An ANN facilitates the ability to learn complex nonlinear relationships between input and output parameters. Thanks to the powerful potential (massive parallelism, generalization capacity and fault-tolerance), ANN has been widely used in fields like pattern recognition, reliability analysis, classification, ship motion control and prediction. The basic architecture of ANN consists of single input, hidden and output layer, with each layer containing one or more neurons, in addition to bias neurons connected to the hidden and output layers. The back-propagation (BP) algorithm is the most widely used learning algorithm for ANN, which is a self-adapted learning procedure that minimizes the error between the desired and the predicted outputs. The learning process consists of two parts: feed-forward and backward pass. The output of ANN is calculated in the process of feed-forward pass, with the output error propagated backward to adjust the weights and bias of the ANN. The number of hidden layer nodes and the maximum iteration number should be carefully chosen to overcome the over-fitting and under-fitting problems. Over-fitting means that a trained ANN has weak capability of generalization. An over-fitted ANN usually has a good prediction capability over train samples, but has a bad prediction capability over test samples. Under-fitting means that a trained ANN is too simple to be capable of representing the relationship between input parameters and output targets. An under-fitted ANN usually has bad prediction capabilities over both training and testing samples.

Sensitivity Analysis

SA could be implemented in either local or global manner. The LSA explore the response of the model output to a small change of the parameter from its nominal value. Garson algorithm is one of the popular LSA algorithms [9]. This method has shown to be computational efficient and conceptually simple when quantifying the relative importance of input parameters. It has been used in some ship motion prediction applications, such as the work in [5, 6, 10]. Local sensitivity index is calculated at the nominal point or a fixed point, which is not representative for all inputs in the whole parameter space. In addition, the LSA do not explore the interactions between input parameters.

In contrast, a GSA estimates the effect of input parameters across the whole input parameter space. GSA is generally divided into four categories: Traditional methods, Analysis of Variance methods (ANOVA) methods, Derivative-Based Methods and Surrogate-Based Methods. ANOVA methods are also called variance-based methods, which makes ANOVA decomposition of model response variances into the contributions from individual parameters and their interactions. Cukier, et al. presented Fourier Amplitude Sensitivity Test (FAST) [11]. Later, Salteli et al. introduces a global, quantitative, model independent SA method for calculating both main effect and total effect indices based on the FAST — extended FAST (EFAST) [12]. EFAST is model independent, which can be used in ANN based prediction. Currently, most of the study only focuses on studying either LSA or GSA in ANN based ship prediction model. There is not a systematic comparison between them. In this study, efforts are made to combine the ANN with the Garson algorithm and the EFAST algorithm respectively, aiming to find out which one is preferable for nonlinear ship motion prediction.

SIMPLIFICATION OF ANN MODEL VIA SENSITIVITY ANALYSIS

System Structure

This paper aims to construct a compact ANN model for ship motion prediction using the SA approach. The main idea is to use the SA method to evaluate the importance of each input and select the inputs according to their importance. The input selection procedure consists of four components: data cleaning, surrogate model, SA and result visualization. Data cleaning is to minimize the affection of noisy, redundant information of sensor data on further analysis and modeling. In general, it is difficult to estimate the contribution of each input parameter and the interaction

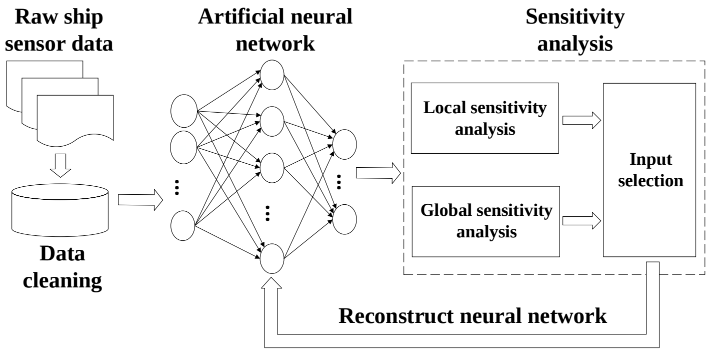

FIGURE 1. Input selection procedure.

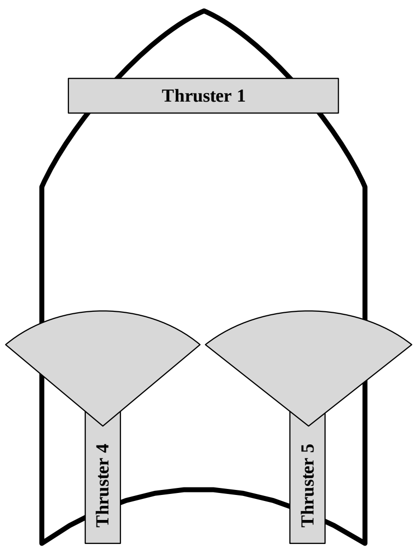

FIGURE 2. Illustration of used ship model.

TABLE 1. Recorded ship data specification

Module	Parameter	Unit
Ship-environment Status	Surge_vel	[m/s]
	Sway_vel	[m/s]
	Yaw_vel	[m/s]
	Roll_vel	[m/s]
	Pitch_vel	[m/s]
	Pos_x	[m]
	Pos_y	[m]
	Heading	[deg]
	Roll	[deg]
	Pitch	[deg]
Thrust1 Status	Percent	[%]
	Shaft_speed	[RPM]
	Pitch_angle	[deg]
	Force	[N]
	Yaw_moment	[Nm]
	Consumed_power	[W]
Thrust4 Status	Percent	[%]
	Shaft_speed	[RPM]
	Pitch_angle	[deg]
	Force	[N]
	Yaw_moment	[Nm]
	Consumed_power	[W]
Thrust5 Status	Percent	[%]
	Shaft_speed	[RPM]
	Pitch_angle	[deg]
	Force	[N]
	Yaw_moment	[Nm]
	Consumed_power	[W]

of input variables to output from those data directly. Surrogate-based methods provide an analytic approach to construct mathematical model or prediction model from those sensor data. The widely used surrogate models, such as Kriging [13], Gaussian surrogate model [14], the Radial Basis Function surrogate models [15] and ANN surrogate model [16] can be effectively used for practical SA. ANN plays the dual role in our project for both prediction model and surrogate model of SA. The LSA and GSA are utilized to calculate sensitivity index of each input parameter, respectively. Finally, the result plotting has been realized in the result visualization component.

As is presented in Figure. 1, firstly, the ANN was employed as the surrogate model to generate the ship prediction behavior model. The model contains all the relevant input parameters described in Table 1. The ANN is trained by ship simulation data to achieve certain prediction accuracy in advance. Secondly, LSA methods such as Garson algorithm, GSA methods like EFAST, are applied to calculate the influence of input parameters on the output variables based on the model. Thirdly, users can select the importance of input factors based on LSA or GSA for different applications. Those left input factors will feedback to neural network construction, and the ANN with appropriate number of inputs would be the prediction model.

The case ship model used is equipped with one tunnel thruster in the bow, and two main propellers with rudders at the stern, as shown in Figure. 2. Since the rudder of the main propeller is fixed during the maneuvering, it degenerates as the tunnel thruster. In this vessel, four data modules are monitored and stored: the ship-environment data module, and the three thruster data modules, as shown in Table 1. Those parameters in ship-environment data module are the status of case ship. For example, Surge_vel represents the surge velocity; Sway_vel stands for the sway velocity. Corresponding to Figure. 2, there are three groups thrust parameters which describe the working status of each thrust. In this paper, heading of case ship is chosen as the output parameter of prediction model. The definition of heading is within $[0^\circ, 360^\circ]$ originally. Therefore it may appear discontinuity in the corresponding sensor data. We applied the algorithm

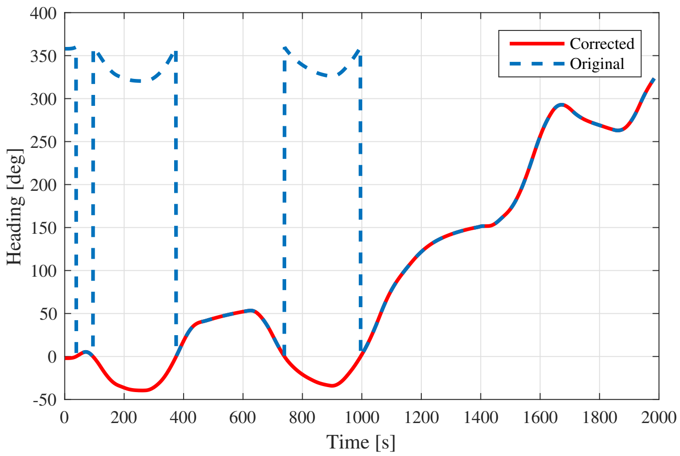

FIGURE 3. Ship heading correction.

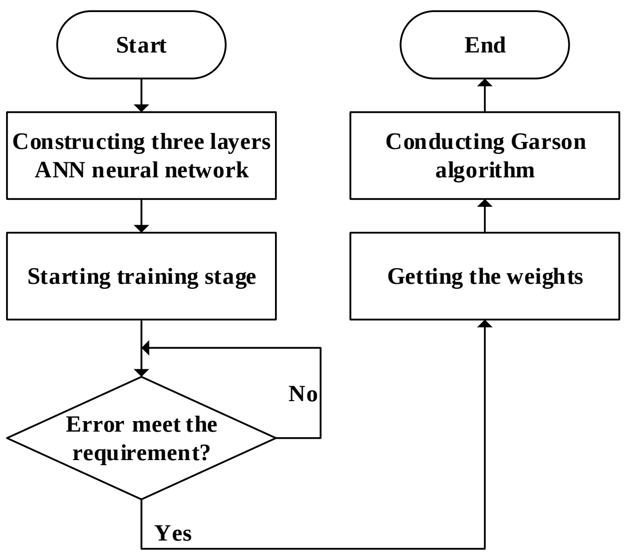

FIGURE 4. Flow chart of ANN-Garson.

in [5] to remove this type of discontinuity. Figure. 3 illustrates the ship heading variance before and after data processing. The blue dotted line in the Figure. 3 is the raw data, and the red line represents the corrected data.

LSA based on ANN

LSA is performed by modifying one of the input values across its entire range at a time, while holding the rest of input values constant. Garson's algorithm is a 'weights' method in SA which is implemented by the connected weights obtained from an ANN model. It provides a quantitative tool by partitioning the neural network connection weights into components associated with each input neuron for calculating the relative importance of each input variable in the network. In this paper, the LSA based on ANN is called ANN-Garson, and we follow the work in [17] for LSA calculation:

$$S_{ik} = \frac{\sum_{j=1}^{L} \left(|\omega_{ij} \upsilon_{jk}| / \sum_{r=1}^{N} |\omega_{rj}|\right)}{\sum_{r=1}^{N} \sum_{j=1}^{L} \left(|\omega_{ij} \upsilon_{jk}| / \sum_{r=1}^{N} |\omega_{rj}|\right)} \tag{1}$$

where S_{ik} is the sensitive contribution of the input i to output k; N is the number of the neurons in the input layer; L is the number of the neurons in the hidden layer; ω_{ij} is the connected weight between the neuron i in the input layer and the neuron j in the hidden layer; υ_{jk} is the connected weight between the neuron j in the hidden layer and the neuron k in the output layer. In this study, a BP neural network model is built upon the relationship between the predictive attribute and its sensitivity factors in ship motion model. All the sensitivity factors were analyzed with Garsons algorithm based on the connection weights of the neural network model. Figure. 4 illustrates the flow chart of ANN-Garson. A neural network is constructed with three layers and trained with adequate precision. ANN-Garson is conducted for finding those important input factors with the weights of each layer of neural network.

GSA based on ANN

Many different GSA methods have been developed over the years [8]. The global method EFAST is a milestone for global SA of nonlinear models. EFAST was presented for SA of multi-parameter nonlinear model, in which conditional variances are represented by coefficients from the multiple Fourier series expansion of the response function and the ergodic theorem is applied to transform the multi-dimensional integral into a one-dimensional integral in evaluation of the Fourier coefficients. The EFAST method is capable of computing main effect (also called first-order sensitivity index) and the total effect of each parameter to the response variance. EFAST is model form independent, that is to say, it can be employed for any model.

Let's consider the model $Y = f(X_1, X_2, ..., X_n)$, where the $X_1, X_2, ..., X_n$ is the n input variables. Here, the model Y can be either the analytical representation or the computational model. For the k-th input variable X_k, it can relate to the a frequency ω_k in EFAST [18]. The widely used transformation function is defined as follows:

$$X_\mathrm{k}(s) = \frac{1}{2} + \frac{1}{\pi} \arcsin(\sin(\omega_k s)) \tag{2}$$

where, s is a scalar variable varying in the range between $-\pi$

and π, ω_k is the frequency related to X_k. If an appropriate set of integer frequencies is chosen, the model Y can be expressed as:

$$f(s) = f(X_1(s), X_2(s), ..., X_k(s), ...X_n(s)) \tag{3}$$

The model function f can be expanded in Fourier series of the form:

$$f(s) = \sum_{i=-\infty}^{+\infty} (A_i \cos(\omega_i s) + B_i \sin(\omega_i s)) \tag{4}$$

where the Fourier coefficients A_i and B_i are defined as

$$A_i = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) \cos(\omega_i s) ds$$

$$B_i = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) \sin(\omega_i s) ds$$

Based on the Parsevals theorem, the variance of Y states that:

$$D_Y = Var(Y) = 2 \sum_{k=1}^{+\infty} (A_k^2 + B_k^2) \tag{5}$$

The portion of the variance of Y by X_k alone can explained that:

$$D_k = Var_{X_k}[E(Y|X_k)] = 2 \sum_{k=1}^{+\infty} (A_{k\omega_k}^2 + B_{k\omega_k}^2) \tag{6}$$

where $A_{k\omega_k}$ and $B_{k\omega_k}$ denote the Fourier coefficients for the fundamental frequency and its higher harmonics $k\omega_k$. Consequently, the main effect of k-th input variable is given by:

$$S_k = \frac{D_k}{D_Y} = \frac{Var_{X_k}[E(Y|X_k)]}{Var(Y)} = \frac{2\sum_{k=1}^{+\infty} (A_{k\omega_k}^2 + B_{k\omega_k}^2)}{Var(Y)} \tag{7}$$

Inspired from [7] and [12], the ANN-EFAST can be implemented using the following procedure:

Algorithm 1

procedure

1) choosing the inputs and logging the number of input D

2) normalizing the inputs and the outputs in the range$[-1, 1]$ using for instance $X_i = (x_i - a_i)/b_i$, with $a_i = \min(x_i) + \max(x_i)/2$ and $b_i = \max(x_i) - \min(x_i)/2$.

3) selecting the number of hidden units and the learning parameters (bias, epochs, . . .).

4) starting the training stage.

5) Once the training is finished, choosing the interference factor $M = 4$, number of samples N, calculating the max frequency: $\omega_{\max} = (N-1)/(2*M)$.

6) Setting the frequency ω_p for the remaining input factors.

for $i = 1 \to D$ **do**

  $\omega_p[i] = \omega_{\max}/(2*M*i)$

7) Calculating scalar variable s.

for $i = 0 \to N$ **do**

  $s[i] = 2*\pi/N*i$

8) Sampling, $\omega 2$ is the sample frequency.

for $i = 0 \to D$ **do**

  $\omega 2[i] \leftarrow \omega_{\max}$

  $idx \leftarrow 1, . . . , N$ except i

  $\omega 2[idx] \leftarrow \omega_p$

  $l \leftarrow (i*N\ ,\ (i+1)*N)$

  for $j = 0 \to N$ **do**

    $g = 0.5 + \arcsin(\sin(\omega 2[j]*s + 2*\pi*rand))$

    $X[l, j] = g$

9) Model evaluation $Y = Model(X)$, the model here is the neural network.

10) Compute first order sensitivity index for each input.

Algorithm 1 allows to compute the global sensitivity index using EFAST to discover those more important inputs. It is important to notice that the EFAST algorithm takes place after the training stage. As EFAST is model independent, all we have to know is how to compute the output to perform the EFAST analysis. In this way, EFAST can help to check whether important known variables in a model have been correctly considered.

EXPERIMENTS

This section involves three independent experiments. The first two is to compare the proposed methods with some benchmark to verify the feasibility of ANN-EFAST and ANN-Garson, while the last experiment is a case study of applying ANN-EFAST on input selection of ANN for ship heading prediction.

TABLE 2. Comparison in linear system

Algorithm	x_1	x_2
Analytical	0. 997	0. 003
EFAST	0. 995	0. 003
ANN-Garson	0. 499	0. 154
ANN-EFAST	0. 992	0. 016

TABLE 3. Input parameters sensitivity index of Ishigami function

Algorithm	x_1	x_2	x_3
Analytical	0.313	0.442	0
EFAST	0.307	0.444	0
ANN-EFAST	0.299	0.435	0.04
ANN-Garson	0.311	0.256	0.315

Comparison in Linear System

The first test case is a widely used feature selection function [19]:

$$y = x_1 + 0.05x_2 \tag{8}$$

The purpose is to test the performances of ANN-Garson and ANN-EFAST in the linear system. All input parameters are sampled uniformly in the range [-1, 1]. Therefore, the output y is close to the input x_1, i. e., x_1 has a higher sensitivity index compared to x_2.

First,The analytical result was calculated as follows [20]:

$$\begin{aligned}
&E(Y) = E(X_1) + E(X_2) = 0 + 0 = 0 \\
&V(X_1) = E(X_1^2) - E^2(X_1) = \tfrac{1}{2}\int_{-1}^{1} X_1^2 dX_1 - 0 = \tfrac{1}{3} \\
&\approx 0.3333 \\
&V(X_2) = E(X_2^2) - E^2(X_2) = \tfrac{1}{2}\int_{-1}^{1} (0.05X_2)^2 dX_2 - 0 \\
&= 0.0025 \\
&V(Y) = V(X_1) + V(X_2) = 0.3358 \\
&V_{X_1}[E(Y|X_1)] = V(X_1) = 0.3333 \\
&V_{X_2}[E(Y|X_2)] = V(X_2) = 0.0025 \\
&S_1 = \frac{V_{X_1}[E(Y|X_1)]}{V(Y)} \approx 0.9925 \\
&S_2 = \frac{V_{X_2}[E(Y|X_2)]}{V(Y)} \approx 0.0075
\end{aligned}$$

where $E(i)$ is the expectation of i; $V(i)$ is the variance of i; $V_{X_i}[E(Y|X_i)]$ is the variance of the conditional expectation X_i; S_i is the main effect of i. Second, the EFAST was preformed based on [12]. Third, an ANN with x_1 and x_2 as inputs and y as the output using samples from Eq. (8) was constructed and trained for engaging ANN-Garson and ANN-EFAST algorithms. Table 2 shows the result of those algorithms. Similar results are found between the analytical method, the EFAST method and the ANN-EFAST. The ANN-Garson method shows the ability to distinguish the importance of variables but the result is far away from the result of the other three methods. The supposition for this result is that Garson algorithm is one of LSA methods, the best performance will happen in a fixed point.

Comparison in Nonlinear System

The second test case is the Ishigami function with three input parameters [21]. The nonlinear and non-monotonic function is often used in literature as the global sensitivity benchmark methods.

$$\begin{aligned} y = \sin(x_1) + 7\sin^2(x_2) + 0.1{x_3}^4\sin(x_1) \\ x_i \in [-\pi, \pi], i = 1,2,3 \end{aligned} \tag{9}$$

where x_i is uniformly distributed within $[-\pi, \pi]$. For analytical method, the variance of output y and the sensitivity index can be computed as follows:

$$\begin{aligned}
&V(y) = \pi^4/50 + \pi^8/1800 + 1/2 + 49/8 \approx 13.8445 \\
&V_1 = 1/2 + \pi^4/50 + \pi^8/5000 \approx 4.345892 \\
&S_1 = V_1/V(y) \approx 0.3139 \\
&V_2 = 49/8 = 6.125 \\
&S_2 = V_2/V(y) \approx 0.4424 \\
&V_3 = 0 \\
&S_3 = 0
\end{aligned}$$

where the $V(y)$ is the variance of y; V_1, V_2 and V_3 are the variance of input parameter x_1, x_2, x_3, respectively; S_1, S_2 and S_3 are the first sensitivity index of input parameter of x_1, x_2, x_3. For ANN-Garson and ANN-EFAST, again, we trained an ANN with three inputs and one output to fit the Ishigami function. The modified Garson algorithm and EFAST algorithm was then performed on the well-trained ANN. Table 3 shows the comparative result of the analytical method, EFAST algorithm, ANN-EFAST algorithm and ANN-Garson algorithm. It is obvious that the proposed ANN-EFAST method obtains a relative smaller error than that of the ANN-Garson method, which means the proposed ANN-EFAST method also take effects in solving nonlinear problems.

Comparison of Input Selection for Ship Heading Prediction

A case study of SA on ship heading was carried out to find those relative important input parameters in ship motion prediction model. In this experiment, an ANN with 27 attributes as the inputs and the heading attribute as the output was established and trained. Note for continuity purpose, the heading data was processed before importing to the ANN. The hyperbolic tangent is chosen as the activation function. A total of 1984 sets of data under the Levenberg-Marquardt algorithm were employed to train

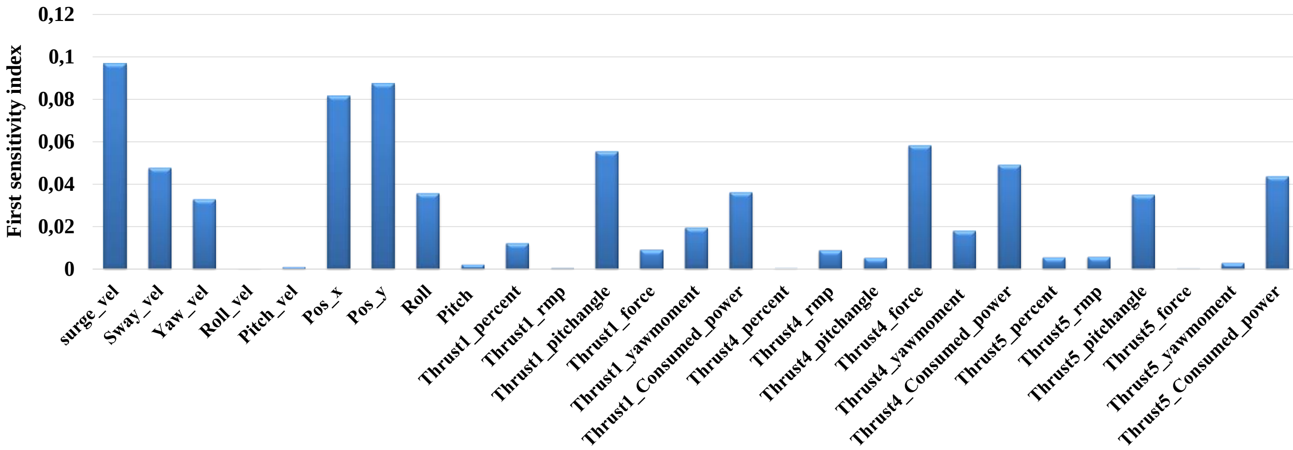

FIGURE 5. Result of ANN-EFAST in ship heading prediction model.

TABLE 4. Performance comparison

Number of hidden nodes	ANN-A		ANN-B		ANN-C	
	Time [s]	MSE	Time [s]	MSE	Time [s]	MSE
16	336.26	2.94	7.94	0.14	173.91	1.35
20	13.09	0.47	7.01	0.14	203.84	0.48
24	9.63	0.62	4.76	0.178	229.66	0.54

the ANN. Once the train stage finished, it is time to preform SA approach on it. Considering the results of the above two tests on both linear and nonlinear systems, the ANN-EFAST method is preferable since the ship motion model is a complex nonlinear model. Figure. 5 shows the results of ANN-EFAST. It is interesting that surge velocity has the highest sensitivity index than the other input parameters for ship heading prediction model. In addition, the position of the ship has also a relative high sensitivity index. This makes sense because the change of ship's position is the result from the integration of surge, sway and yaw velocities, definitely correlating to the ship heading. Here, those input parameters, with the corresponding first sensitivity index exceeds 0.02, are selected. This indicates there are 12 of 27 input parameters used to construct the new ANN.

To verify the importance of the selected input parameters from ANN-EFAST, three ANNs, i. e., A—the ANN with full inputs, B—the ANN with inputs based on ANN-EFAST, C—the same ANN from B but with one more input parameter removed, were compared. We focused on different number of hidden nodes for the three ANNs in terms of computational time and mean square error (MSE). Each comparison is repeated five times to ensure the predictive convergence. The average comparative result is illustrated in Table 4. ANN-A works well owing to the full input, except the time consuming due to computational complexity. Another weakness of ANN-A is that the training error is lager under the same training conditions with ANN-B and ANN-C. ANN-B in the case of finding the suitable input parameters has been greatly improved. In contrast, ANN-C reflects that excessive reduction of input parameters results in the decrease of performance of ANN-C regarding to both the training time and the MSE. As a result, ANN-B is more efficient and accurate in cases of different number of hidden layer nodes. Note that from Figure 5, the sum of first sensitivity index of all input parameters is 0.753, less than 1, which means the interaction of input parameters is also significant. Therefore, SA on ANN model of ship heading prediction should be analyzed not only on the single influence of each input, but also on the complexity nature of input parameter interaction. Our future work will focus on this aspect, especially for quantifying input parameters interaction for the predictive model.

CONCLUSION

This work presents an ANN based surrogate model for Garson and EFAST sensitivity estimation. First, an ANN is constructed as a surrogate for the original model or the original sensor data. Taking the advantage of ANN for fast convergence, the ANN-Garson and the ANN-EFAST are proposed, which has the ability for local and global sensitivity estimation, respectively. Comparison results from the benchmark illustrate that the ANN-EFAST presents a relatively better SA performance than the ANN-Garson for both linear and nonlinear problems. The application to the ship heading prediction model emphasizes the general nature of ANN-EFAST, and demonstrates its usability in the complex, non-linear system. Particularly, for those only input-output samples are available and the underlying model is unavailable or cannot be explicitly expressed, our methods offer a solution to estimate the sensitivity index. Considering this paper only concerns the first order sensitivity index of each input factor, future work will turn to focus on the interaction between input parameters of ship prediction model.

ACKNOWLEDGMENT

This research is partially supported by the project "An Approach toward Optimal Control of Ship Manoeuvring in Offshore Operations" funded by RFF Midt-Norge, Norway (project no: 256926), and partially supported by the National Natural Science Foundation of China (Grant no: U1509207).

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