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Roll motion prediction using a hybrid deep learning and ARIMA model

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Abstract

Autoregressive Integrated Moving Average (ARIMA) is one of the linear model that is good, flexible, and easy to use in univariate time series analysis and forecasting. Some research activities in time series forecasting also suggest Artificial Neural Network (ANN) model as an alternative nonlinear model for forecasting. ARIMA model has a good ability to capture the linear pattern while the ANN model is good to capture the nonlinear pattern. ARIMA and ANN models have been widely used in the prediction of roll motion. ARIMA and ANN can also be combine as a hybrid model to take advantage of the ability of ARIMA and ANN models in linear and nonlinear modeling compared to ARIMA and ANN model. In this paper, we adapt the hybrid methodology to combine ARIMA and Deep Neural Network (DNN) model, an ANN model with multiple hidden layers. The real dataset used is the roll motion of a Floating Production Unit (FPU). The empirical results show that the DNN-ARIMA hybrid model is the best model for predicting the roll motion compared to the non hybrid models and very effective to improve forecast accuracy.

Keywords: Arima, deep learning, forecasting, hybrid, roll motion, time series

1. Introduction

Roll motion is one of the ship motion that is the most frequently studied. The ship safety can be analyzed based on the roll motion. The purpose is to prevent the danger of the ship, e.g. ship capsizing [6]. The rolling motion can also cause damages to ship containers. Therefore, the prediction of roll motion is the important thing in order to understand the stability of the ship. The prediction of ship motion can be done by several approaches. One of them is time series forecasting.

In time series modeling, Autoregressive integrated moving average (ARIMA) is one of the popular time series models [25, 12]. It has been widely used in time series forecasting. ARIMA is a general form of several time series processes, such as pure autoregressive (AR), pure moving average (MA), combination of AR and MA (ARMA), and

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ARMA with differencing (ARIMA). Since ARIMA is a linear model, it is assumed that the data follows a linear pattern. However, the data in real problems does not always follow linear pattern only. The linear approximation is not always satisfactory to forecast with good performance as well.

Artificial neural network (ANN) is an alternative nonlinear model that has been extensively studied and used in time series forecasting [24]. Their capability in nonlinear modeling is the major advantage of ANN model. It is not necessary to specify a particular model form. ANN model is adaptively formed based on the features presented from the data. For many empirical data sets where no theoretical guidance is available to suggest an appropriate data generating process, this data-driven approach is the suitable one [17].

Researches in prediction of ship motion have been studied by using several time series models. Zhang and Ye [26] used ARIMA model to predict the roll motion. Nicolau et al. [13] in their research used ANN model to predict the roll motion of a conventional ship. Different training data sets and noise conditions were used to analyze the neural architecture. The results showed that the predictor of ANN model worked well for different levels of the input noise. Khan et al. [8] have used both ARIMA and ANN models to predict the roll motion. The ARIMA model used was ARIMA(15,0,1) and the ANN model used was feedforward neural network with the combination of conjugate gradient (CG) algorithm and genetic algorithm (GA). The results showed that ANN model had a better performance than ARIMA model in predicting the roll motion. Several recent researches also shown that the roll prediction using ANN based model is still satisfactory and powerful [20, 23].

ARIMA and ANN can also be combined to form a hybrid model in order to obtain a better forecasting performance. Hybrid method combines ARIMA model and ANN model to obtain the advantages both of ARIMA and ANN models. Zhang [25] introduced the ARIMA and ANN hybrid model and showed that the hybrid model is very effective to improve the forecast accuracy compared with the separated models. Hybrid model has the good ability in capturing the linear pattern (from ARIMA model) and the nonlinear pattern (from ANN model). Another hybrid method is also conducted by Puspitasari et al. [16] using ARIMA and adaptive neuro-fuzzy inference system (ANFIS) models, for which it results was also satisfactory. Many studies also shown that deep neural network (DNN) model, also called deep learning model, an ANN with multiple hidden layers, has been widely applied for forecasting task and resulted in great performance with high accuracy [2, 9, 14, 15, 19, 27]. In this paper, we will adapt the hybrid method to combine ARIMA model and DNN for predicting or forecasting the roll motion. The hybrid DNN-ARIMA model is then compared to both ARIMA and DNN models. The results of the forecast performance and the forecast accuracy are then discussed.

2. Time Series Models

Time series analysis is the analysis of observational data that occurs in a time sequence and a fixed time interval. Time series analysis consists of a method for analyzing time series data to find the pattern and the characteristics of the data. The application of time series analysis is for forecasting task [11]. Forecasting is done by predicting the future value based on the value of the previous observations. There are many time series models that have been developed. ARIMA is the most popular one. It is one of the linear time series models. The linear models have been applied in many researches because of their simplicity in understanding and explaining the models as well as they are easy to implement. But, the real problems are often more complex and the data also contains nonlinear pattern. The linear approximation occasionally has a bad performance to model this type of data. Recently, many researches suggest ANN model as an alternative to time series forecasting. Its capability in nonlinear modeling becomes the main strength of ANN.

2.1. The ARIMA Model

ARIMA model is the combination of autoregressive (AR) model, moving average (MA), and the differencing process. General form of ARIMA model is as follows [21]:

$$(1-B)^d Y_t = \mu + \frac{\theta_q(B)}{\phi_p(B)} a_t, \tag{1}$$

where:

- $\phi_p(B) \quad = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$
- $\theta_q(B) \quad = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$
- $BY_t \quad = Y_{t-1}$

Y_t denotes the actual value, B denotes the backshift operator, and a_t denotes the white noise sequence with zero mean and constant variance, $a_t \sim WN(0, \sigma^2)$. $\phi_i(i = 1, 2, .., p)$, $\theta_j(j = 1, 2, ..., q)$, and μ are model parameters. d denotes the differencing order. ARMA is a special case of ARIMA model when $d = 0$. The process of constructing ARIMA model is done by using Box-Jenkins procedure. Box-Jenkins procedure is a procedure with empirical approach that is required to identify the order of ARIMA(p,d,q) model, estimate the parameters, check the model diagnostics, select the best model, and perform the forecasting [1].

2.2. *The Deep Feedforward Networks*

Neural network model has a good ability in modeling the data with nonlinear pattern [25]. It does not require the assumptions in the model building process. The characteristics of the data are more decisive in order to form the model. In time series forecasting and modeling, one of the widely used ANN model is single hidden layer feedforward network [24].

Deep feedforward network or DNN is a feedforward neural network model with more than one hidden layer. It is one of the basic deep learning model [5]. The feedforward network aims to approximate some function f^*. A feedforward network finds the best function approximation by learning the value of the parameters θ from a mapping $y = f(x; \theta)$, where the neural architecture is shown in Figure 1. For example, in terms of time series model, the relationship between the output (Y_t) and the inputs $(Y_{t-1}, Y_{t-2}, ..., Y_{t-p})$ in a DNN model with 3 hidden layers is described in the following equation.

$$Y_t = \sum_{i=1}^{s} \alpha_i g\left(\sum_{j=1}^{r} \beta_{ij} g\left(\sum_{k=1}^{q} \gamma_{jk} g\left(\sum_{l=1}^{p} \theta_{kl} Y_{t-l} \right)\right)\right) + \varepsilon_t, \tag{2}$$

where ε_t is the error term, $\alpha_i(i = 1, 2, ..., s)$, $\beta_{ij}(i = 1, 2, ..., s; j = 1, 2, ..., r)$, $\gamma_{jk}(j = 1, 2, ..., r; k = 1, 2, ..., q)$, and $\theta_{kl}(k = 1, 2, ..., q; l = 1, 2, ..., p)$ are the model parameters called the connection weights, p is the number of input nodes, and q, r, s are the number of nodes in the first, second, and third hidden layers, respectively. Function $g(.)$ denotes the hidden layer activation function. Tanh function is commonly used as the activation function where it lies in the interval $(-1, 1)$ as shown in Figure 2. The function is defined as follows:

$$g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \tag{3}$$

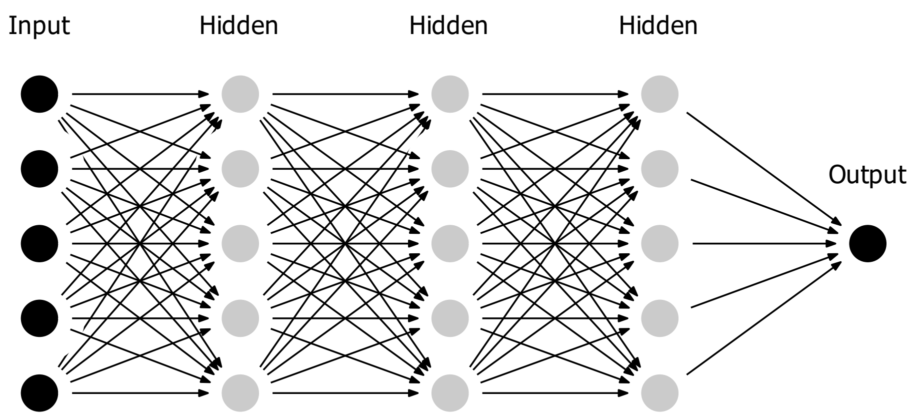

Fig. 1. The neural architecture of DNN with 5 nodes in input layer, 5 nodes in each hidden layer, and a single node in output layer

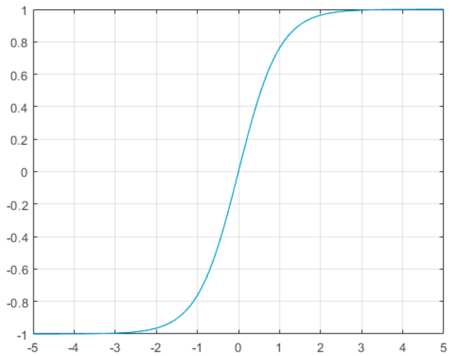

Fig. 2. Tanh function plot

2.3. The Hybrid Model

Hybrid model is a combination (hybrid) model of the linear and nonlinear components. ARIMA model works well when it is used to model the data with linear pattern, while the DNN model works well when it is used to model the data with nonlinear pattern. In real problem, it is not easy to completely know the characteristics of the data. Hence, hybrid methodology can be a good strategy to model the data, with their capability in both linear and nonlinear modeling. This capability is then considered to be able to capture the underlying patterns. Zhang [25] considered to construct a time series model that is composed of a linear component and a nonlinear component. That is,

$$Y_t = L_t + N_t, \tag{4}$$

where L_t denotes linear component and N_t denotes the nonlinear component. Both of the components are obtained from the results of the data estimation. First, we suppose the linear component is obtained from the ARIMA model, then the residuals of the ARIMA model will only contain nonlinear component. Suppose e_t denote the residual vector at t-th time from the linear ARIMA model, then

$$e_t = Y_t - \hat{L}_t, \tag{5}$$

where $\hat{L}_t$ denotes the forecast value for time t from ARIMA model.

Residuals are important in the diagnosis of the sufficiency of linear models. The residuals are then considered to be free of linear pattern. It is because if there are still linear correlation structures left in the residuals, a linear model is not sufficient. Thus, the residuals will only contain the nonlinear pattern. By modeling the residuals using DNN, the nonlinear relationships can be captured. The DNN model for the residuals is presented as follows:

$$e_t = f(e_{t-1}, e_{t-2}, ..., e_{t-n}) + \varepsilon_t, \tag{6}$$

where f is a nonlinear function determined by DNN and ε_t is the random error. Suppose $\hat{N}_t$ denotes the forecast result from equation (6), then the combined forecast is given as follows.

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t. \tag{7}$$

3. Dataset and Methodology

3.1. Dataset

Our study aims to predict the roll motion. Roll motion is one of ship motions, where ship motions consist of six types of motion which are also called as 6 degrees of freedom (6DoF). It is also categorized as a rotational motions, which is illustrated in Figure 3 [22]. The data set used in this study is a series of rolling motion (in degree) of a ship called floating production unit (FPU) in irregular waves. It is generated from a simulation study conducted in Indonesian Hydrodynamic Laboratory. The machine recorded 15 data in every one second. The dataset contains 3250 observations. Time series plot of the data set is shown in Figure 4.

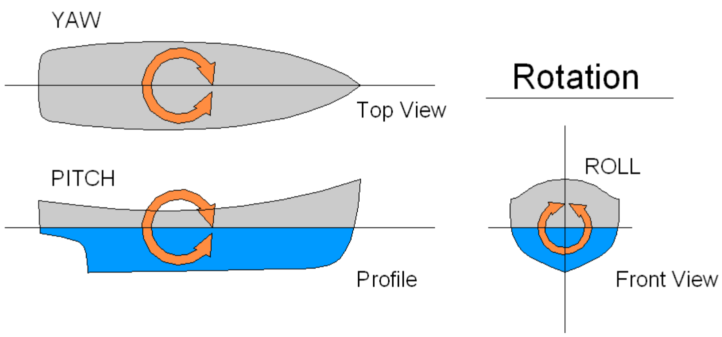

Fig. 3. Rotational ship motions, by Wikipedia Contributors, 2018. Public Domain.

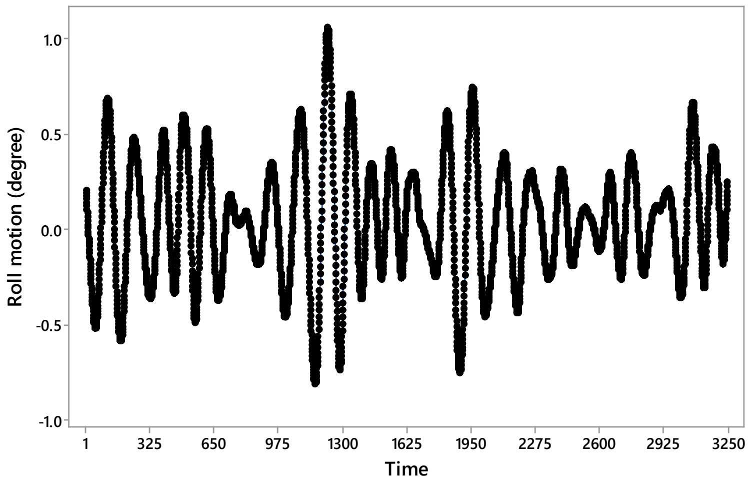

Fig. 4. Time series plot of roll motion

3.2. Methodology

In order to obtain the model and predict the data, we split the data into two parts, which are in-sample and out-of-sample. The data used for modeling is in-sample data. Meanwhile the data used for the prediction is out-of-sample data. We use the first 3000 data as in-sample data. The remaining data is used as the out-of-sample data. In order to calculate the prediction accuracy, we use root mean squared error prediction (RMSEP). RMSEP is calculated using the following equation [4].

$$\text{RMSEP} = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(Y_{n+l} - \hat{Y}_n(l)\right)^2} \tag{8}$$

where L denotes the out-of-sample size, Y_{n+l} denotes the l-th actual value of out-of-sample data, and $\hat{Y}_n(l)$ denotes the l-th forecast.

4. Results and Dicussion

As a first analysis, we conduct Box-Jenkins procedure in order to build the ARIMA model of the roll motion. The model building is implemented via SAS. We use backward elimination procedure in order to select the best model. The best model we obtain for the roll motion is a subset ARIMA model, that is ARIMA([1,2,3,4,9,19,20],0,[1,9]) with zero mean. We also try using R program and apply auto.arima() function in forecast package [7]. This result is not quite satisfactory because it suggests ARIMA(0,0,0) with non-zero mean as the best model. The weakness of auto.arima() function is that it does not consider the subset model in the selection.

The DNN model is then constructed based on the ARIMA model. A nonlinearity test, called Terasvirta test [18], is conducted beforehand and it shows that the data significantly contains nonlinear pattern. We use the lag of AR components in ARIMA([1,2,3,4,9,19,20],0,[1,9]) model as the input layer in both DNN model and DNN-ARIMA hybrid model. The DNN modeling is implemented by using keras library in Python [3]. We conduct the modeling with different number of nodes in hidden layer, from 1 to 10 nodes. Then, we choose the model with minimum RMSEP in out-of-sample forecast as the best model. The results show that the best pure DNN model contains 5 nodes in each hidden layer and the best hybrid model contain 9 nodes in each hidden layer.

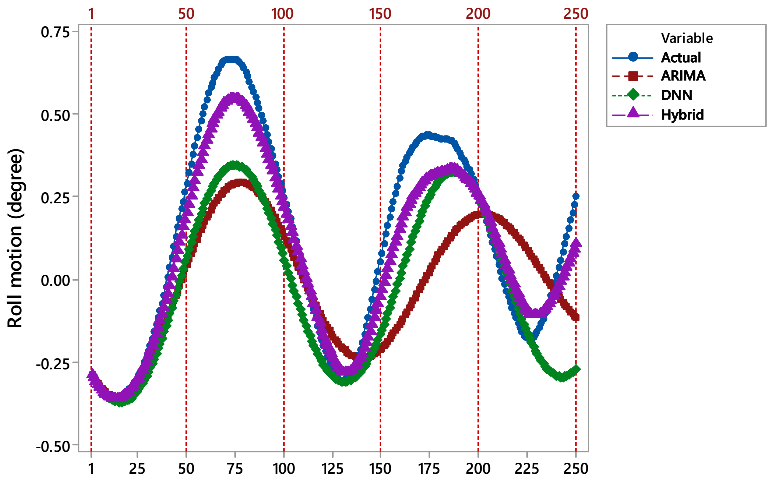

Fig. 5. Forecast comparison between ARIMA, DNN, and hybrid DNN-ARIMA

Table 1. RMSE comparison between ARIMA, DNN, and DNN-ARIMA hybrid models in different forecast horizons

Forecast Horizon	ARIMA	DNN	Hybrid
50	0.095959	0.096846	0.036479
100	0.229144	0.206712	0.074849
150	0.196867	0.182465	0.065721
200	0.245396	0.186452	0.080408
250	0.235718	0.192982	0.078559

In Figure 5, we can see that the predictions of the three models could follow the pattern of the real data. However, the performance of ARIMA model is not as good as the other two models. DNN model and hybrid model show better forecast performances. Visually, the forecast of hybrid model corrects the error forecast of DNN model and improves the forecast accuracy. Table 1 shows that the forecast model of the hybrid has the smallest RMSEP in all forecast horizon. In 250-step ahead forecast, the hybrid model is able to reduce the RMSEP of DNN model by 59,29%. The hybrid model also increases the forecast accuracy of the ARIMA model with higher reduction of RMSEP by 66,67%. These results indicate that the hybrid model is able to significantly improve the forecast accuracy of both ARIMA and DNN models. The ability to capture both linear and nonlinear patterns works well in this case.

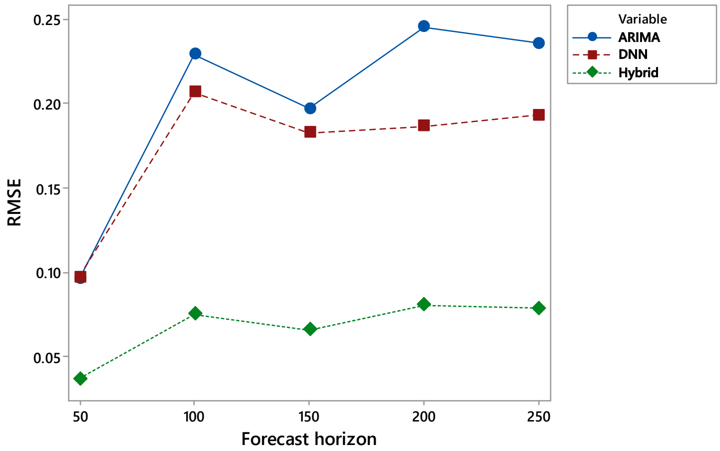

Fig. 6. Plot of RMSE in different forecast horizons

Figure 6 shows the RMSEP changing in different forecast horizons of all models. Let us only consider the hybrid model. The best forecast performance is 50-step forecast. The RMSEP increases in 100-step forecast, but it decreases in 150-step forecast, and it increases again in 200-step forecast. The decreasing occurs again in 250-step forecast. It shows that the RMSEP does not increases monotonically as the forecast horizon increases. The difference of RMSEP between 50-step forecast and 250-step forecast is 0.04208, which we consider that the difference is not sufficiently significant. Therefore, the prediction of roll motion with 250-step (about 17 seconds) ahead is still considerably good.

As Makridakis et al. [10] mentioned that the model forecast performance also depends upon the forecast horizon, where the best model may vary with the forecast horizon. Compared to our results, it is shown that the forecast performance tends to be consistent in the ranking, where the hybrid model outperforms among the others in every forecast horizon. Since we only have three model in our comparison, it might be more interested when we add more models to compare and see if there is variation in performance upon the forecast horizon.

5. Conclusions and Future Works

The ARIMA and DNN models are successful to predict the roll motion. Their forecast are able to follow the pattern of the real data. The hybrid model becomes the best model among these three models with minimum RMSEP. It shows that the hybrid methodology could significantly increase the forecast accuracy of both ARIMA and DNN models. We consider that this method could be the promising technique to improve the forecast performance, especially in roll motion study. There are also many combinations of linear and nonlinear models that can be developed in further research.

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References

[1] Box, G.E., Jenkins, G.M., Reinsel, G.C., Ljung, G.M., 2015. Time series analysis: forecasting and control. John Wiley & Sons.
[2] Chen, Y., He, K., Tso, G.K., 2017. Forecasting crude oil prices: a deep learning based model. Procedia Computer Science 122, 300–307.
[3] Chollet, F., et al., 2015. Keras. https://keras.io.
[4] De Gooijer, J.G., Hyndman, R.J., 2006. 25 years of time series forecasting. International journal of forecasting 22, 443–473.

[5] Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. MIT Press.
[6] Hui, L.H., Fong, P.Y., 2010. A numerical study of ships rolling motion, in: Proceedings of the 6th IMT-GT Conference on Mathematics, Statistics and its Applications, pp. 843–851.
[7] Hyndman, R.J., Khandakar, Y., 2008. Automatic time series forecasting: the forecast package for R. Journal of Statistical Software 26, 1–22. URL: http://www.jstatsoft.org/article/view/v027i03.
[8] Khan, A., Bil, C., Marion, K., Crozier, M., Melbourne, M., Melbourne, M., 2004. Real time prediction of ship motions and attitudes using advanced prediction techniques, in: Congress of the International Council of the Aeronautical Sciences. International Council of the Aeronautical Sciences.
[9] Liu, L., Chen, R.C., 2017. A novel passenger flow prediction model using deep learning methods. Transportation Research Part C: Emerging Technologies 84, 74–91.
[10] Makridakis, S., Hibon, M., 2000. The m3-competition: results, conclusions and implications. International journal of forecasting 16, 451–476.
[11] Makridakis, S., Wheelwright, S.C., Hyndman, R.J., 2008. Forecasting methods and applications. John wiley & sons.
[12] Miftahuddin, Helida, D., Sofyan, H., 2017. Periodicity analysis of tourist arrivals to banda aceh using smoothing sarima approach, in: AIP Conference Proceedings, AIP Publishing. p. 050042.
[13] Nicolau, V., Palade, V., Aiordachioaie, D., Miholca, C., 2007. Neural network prediction of the roll motion of a ship for intelligent course control, in: Knowledge-Based Intelligent Information and Engineering Systems, Springer. pp. 284–291.
[14] Qin, M., Li, Z., Du, Z., 2017. Red tide time series forecasting by combining arima and deep belief network. Knowledge-Based Systems 125, 39–52.
[15] Qiu, X., Ren, Y., Suganthan, P.N., Amaratunga, G.A., 2017. Empirical mode decomposition based ensemble deep learning for load demand time series forecasting. Applied Soft Computing 54, 246–255.
[16] Suhartono, Puspitasari, I., Akbar, M.S., Lee, M.H., 2012. Two-level seasonal model based on hybrid arima-anfis for forecasting short-term electricity load in indonesia, in: Statistics in Science, Business, and Engineering (ICSSBE), 2012 International Conference on, IEEE. pp. 1–5.
[17] Suhartono, Saputri, P.D., Amalia, F.F., Prastyo, D.D., Ulama, B.S.S., 2017. Model selection in feedforward neural networks for forecasting inflow and outflow in indonesia, in: Communications in Computer and Information Science, Springer. pp. 95–105.
[18] Teräsvirta, T., Lin, C.F., Granger, C.W., 1993. Power of the neural network linearity test. Journal of Time Series Analysis 14, 209–220.
[19] Voyant, C., Notton, G., Kalogirou, S., Nivet, M.L., Paoli, C., Motte, F., Fouilloy, A., 2017. Machine learning methods for solar radiation forecasting: A review. Renewable Energy 105, 569–582.
[20] Wang, Y., Chai, S., Khan, F., Nguyen, H.D., 2017. Unscented kalman filter trained neural networks based rudder roll stabilization system for ship in waves. Applied Ocean Research 68, 26–38.
[21] Wei, W.W.S., 2006. Time series analysis: univariate and multivariate methods. Pearson Addison Wesley.
[22] Wikipedia contributors, 2018. Ship motions — Wikipedia, the free encyclopedia. https://en.wikipedia.org/w/index.php?title=Ship_motions&oldid=833428351. [Online; accessed 15-April-2018].
[23] Yin, J.c., Zou, Z.j., Xu, F., 2013. On-line prediction of ship roll motion during maneuvering using sequential learning rbf neuralnetworks. Ocean engineering 61, 139–147.
[24] Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks:: The state of the art. International journal of forecasting 14, 35–62.
[25] Zhang, G.P., 2003. Time series forecasting using a hybrid arima and neural network model. Neurocomputing 50, 159–175.
[26] Zhang, X.l., Ye, J.w., 2009. An experimental study on the prediction of the ship motions using time-series analysis, in: The Nineteenth International Offshore and Polar Engineering Conference, International Society of Offshore and Polar Engineers.
[27] Zhao, Y., Li, J., Yu, L., 2017. A deep learning ensemble approach for crude oil price forecasting. Energy Economics 66, 9–16.