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Forecasting the Baltic Dry Index by using an artificial neural network approach

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Abstract: The Baltic Dry Index (BDI) is a robust indicator in the shipping sector in terms of global economic activities, future world trade, transport capacity, freight rates, ship demand, ship orders, etc. It is hard to forecast the BDI because of its high volatility and complexity. This paper proposes an artificial neural network (ANN) approach for BDI forecasting. Data from January 2010 to December 2016 are used to forecast the BDI. Three different ANN models are developed: (i) the past weekly observation of the BDI, (ii) the past two weekly observations of the BDI, and (iii) the past weekly observation of the BDI with crude oil price. While the performance parameters of these three models are close to each other, the most consistent model is found to be the second one. Results show that the ANN approach is a significant method for modeling and forecasting the BDI and proving its applicability.

Key words: Baltic Dry Index, forecasting, artificial neural network, crude oil, shipping industry

1. Introduction

The Baltic Dry Index (BDI), as a shipping and global economic index, has been produced daily by the London-based Baltic Exchange since 1985. It indicates the changes in freight rates in the transport of raw materials such as iron ore, coal, and grain considering 23 time charter-based shipping routes for Handysize (15,000–35,000 deadweight tons (DWT)), Supramax (50,000–60,000 DWT), Panamax (65,000–80,000 DWT), and Capesize ($>$150,000 DWT) dry bulk carriers (Baltic Dry Index Data - Lloyd's List Intelligence). The BDI shows the demand for cargo capacity and supply of dry bulk carriers. According to the Baltic Exchange, the BDI also predicts future economic growth indirectly by considering the capacity of transported raw materials as inputs to production of other commodities [1].

Forecasting is vital for all industries, but more so for maritime industry. Change in the shipping market is stochastic and fluctuating because events generally occur suddenly and unpredictably [2]. Due to the advancement in technology, the shipping industry is becoming more prosperous in analyzing the shipping indices, from which meaningful results are referred by investors. Internal and external factors along with the inherent volatility should be explored by an outstanding and rational method.

In recent years, artificial neural networks (ANNs) have become extremely popular for prediction and

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forecasting. The objective of this study is to develop neural networks that can forecast the BDI over the next time step of 1 week based on previous observations. Due to the fluctuation in historical data, modeling of the BDI is very complex and time-consuming. Therefore, an ANN is used as one of the most accurate and widely applied forecasting models.

In the literature, there exist several forecasting applications using ANNs for different purposes in diverse fields. Forecasting, classification, data processing, robotics, control, etc. are some of the examples [3,4]. The ANN approach is implemented for various problems (traffic, freight rate forecasting, etc.) in the shipping sector by several scholars. For example, forecasting of weekly freight rates for a 1-year time charter 65,000 DWT bulk carrier was studied in [2]. Similarly, forecasting of tanker freight rate using neural networks was carried out in [5]. Forecasting of the Suez Canal traffic was conducted in [6]. Many other studies [7–9] showed that ANNs are powerful modeling tools for forecasting of an intended problem.

In the literature, there are several papers that use BDI data as a reliable and effective source. For instance, the effects of trade expansion over gross domestic product per capita can be estimated by using BDI data. Bildirici et al. [10] investigated the relationship between economic growth and BDI as a major economic policy indicator by using Markov-switching vector autoregressive models. The volatility of the BDI was analysed based on empirical mode decomposition in [11]. Zeng et al. [12] proposed empirical mode decomposition for forecasting of the BDI. They decomposed the BDI into three distinct components representing short-term changes, long-run trends, and external shocks, respectively. Another BDI forecasting model was proposed by Jianmin et al. [13]. In their study, a support vector machine was implemented and trends with the forecast precision were modeled. Another BDI forecasting approach using fuzzy sets, gray theory, and ARIMA was employed by Wong[14]. Forecasting of dry cargo freight rates using bivariate long-term fuzzy time series forecasting was studied by Duru et al. [15]. In the study of Uyar et al. [16], trained recurrent fuzzy neural networks were used for forecasting long-term dry cargo freight rates. The cross-correlations between BDI and crude oil price (COP) were studied by Ruan et al. [17].

In the paper by Zeng et al., ANN and VAR (vector autoregression) methods were compared with each other. Results showed that the ANN method outperformed VAR [12]. Azadeh et al. used an ANN for forecasting annual electricity consumption. The accuracy of the ANN results over regression models were validated using ANOVA. The results showed that the ANN better estimated values for total electricity consumption [18]. Pino et al. [19] developed an ANN model for forecasting the next-day price of electricity in the Spanish energy market. ANN forecasts were compared to the Box–Jenkins ARIMA forecasting method. Results showed that neural nets performed better than ARIMA models [19]. The above-mentioned papers proved that ANNs have superiority over other methods including VAR, ANOVA, and Box–Jenkins.

In this study, we aim to establish an ANN approach for BDI forecasting. Data from 2010–2016 are used to forecast the BDI. This study involves more comprehensive data compared to the above-mentioned papers. Seven-year daily data (in total 1735 days) are transformed to average weekly data. To the best of our knowledge, the present research is the first study using a pure ANN for BDI forecasting. Three different ANN models are constructed: (i) the past weekly observation of the BDI, (ii) the past two weekly observations of the BDI, and (iii) previous weekly observations of the BDI with COP.

The remainder of this study is designed as follows. Section 2 presents the materials and ANN modeling. Section 3 discusses the results of three different models developed in this study. A systematic comparison is conducted in terms of performance analysis. Finally, Section 4 concludes the paper.

2. Materials and methods

2.1. Data collection

Data related to construction of ANN models are collected from two different sources. The BDI data are gathered from Quandl (Baltic Dry Index Data - Quandl). The COP data are collected from the Federal Reserve Bank of St. Louis (Crude Oil Prices - Federal Reserve Bank of St. Louis). The BDI data contain the weekly average value of the BDI from 01/10/2010 to 18/12/2016, corresponding a total of 360 weeks. COPs are also obtained in the same way. Figures 1 and 2 show average weekly data of the BDI and COP, respectively.

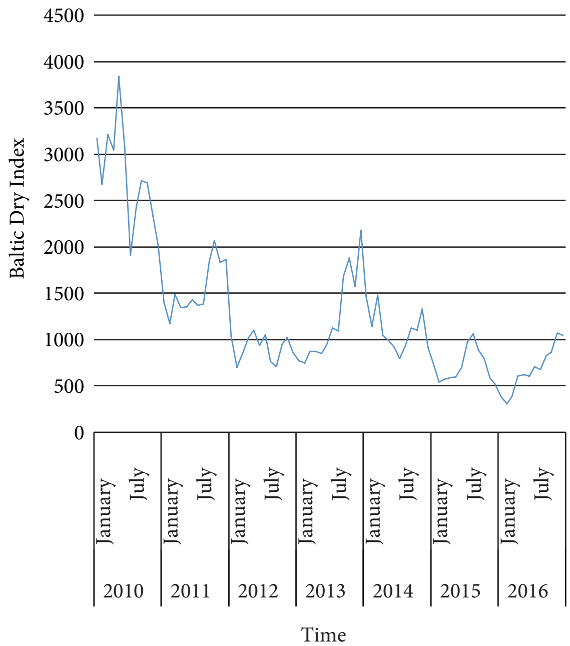


Figure 1. BDI between 2010 and 2016.

It can be observed from Figures 1 and 2 that fluctuations in the time series of the BDI and COP have large amplitude, and they represent irregular trends. Although they have decreasing trends in general, the future trend is not easily predictable because the differences between current and past values are not linear, and they are not directly related to each other. Traditional statistical regression approaches cannot easily handle such complex data (e.g., BDI); therefore, reliable and strong tools (i.e. artificial intelligence) are most preferred in the literature.

2.2. Modeling with artificial neural network

In recent years, neural networks have become popular in scientific and business fields [6]. One of the most attractive characteristics of a neural network is that it can learn from past experiences and then enable generalization of the processed data depending on what it has learned. This capability forms the basis for the neural network's potential in forecasting.

A neural network consists of an input layer, an output layer, and one or more hidden layers. Learning occurs during the process of weight revision such that outputs of the neural network match the desired targets [5]. One of the important problems that may arise during the training of an ANN is overfitting. Early stopping by using a validation set is one of the practical solutions for this problem. A set of 360 samples of data

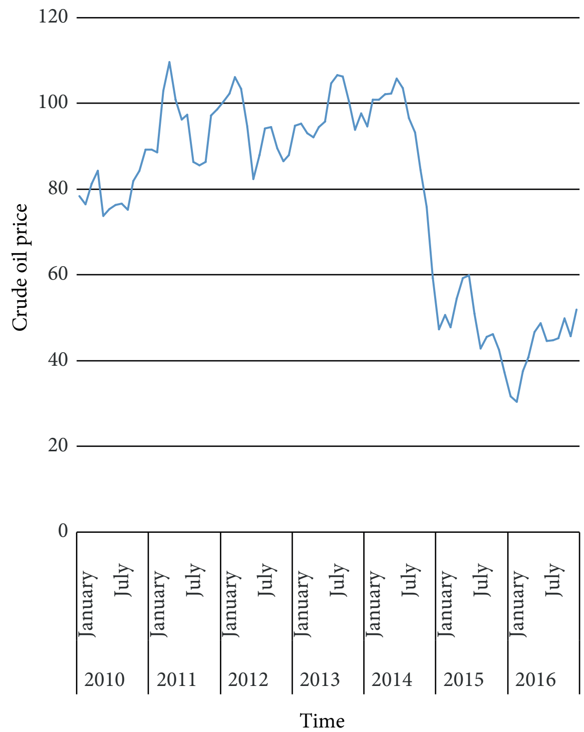


Figure 2. COP between 2010 and 2016.

was prepared for the present study. Among the gathered set of data, data of 288 weeks (from 01/10/2010 to 19/07/2015) are used for the training, data of 36 weeks (from 26/07/2015 to 03/04/2016) are used for validation, and the remaining data of 36 weeks (from 10/04/2016 to 18/12/2016) are set aside for testing.

A backpropagation network using the Levenberg–Marquardt (LM) algorithm is used to train the network. The LM algorithm is a variation of Newton's method that is designed for minimizing functions that are sums of squares of other nonlinear functions. It can be thought of as a combination of the steepest descent and Gauss–Newton methods [3,4]. In order to acquire the nearest output values to collected data, different numbers of neurons (1–15) in the hidden layer are tried. The *logsig* activation function is employed in the hidden layer and the *purelin* activation function is utilized in the output layer. General definitions are expressed in the following equations:

$$logsig\,(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$purelin\,(x) = x \tag{2}$$

As mentioned above, the validation data set is used to solve the overfitting problem, and maximum validation failure is set to 50. In the training process, learning rate and momentum coefficient are taken as 0.4 and 0.6, respectively. Normalized values of input and output are taken between zero and unity. The mean square error (MSE) is determined as a network performance function. The statistical methods of mean absolute percentage error (MAPE) and coefficient of determination (R^2) are used for network comparisons. These are expressed by the following equations:

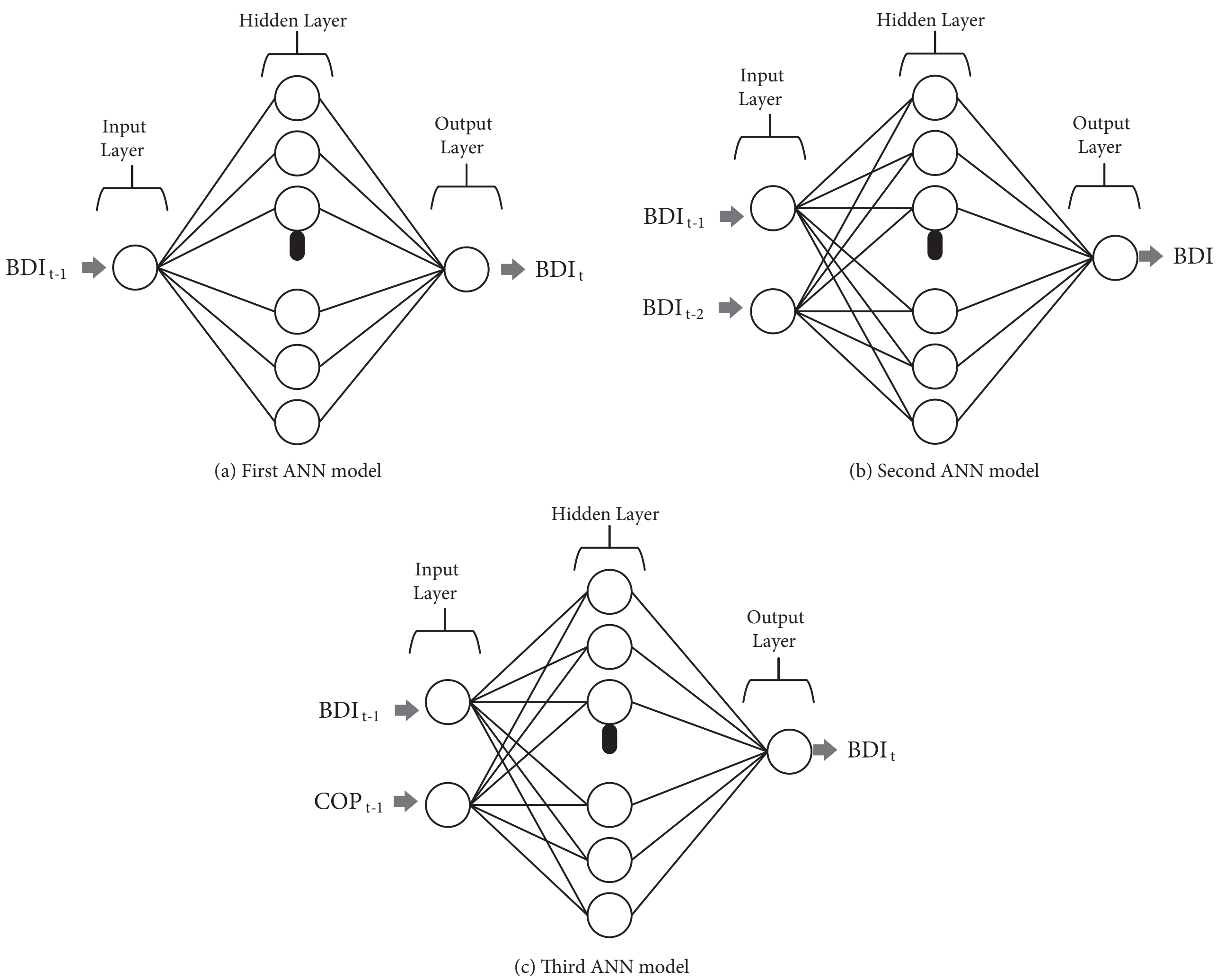
$$MSE = \frac{1}{n}\sum_{i=1}^{N}(t_i - o_i)^2 \tag{3}$$

$$MAPE = \frac{1}{n}\sum\left|\frac{t_i - o_i}{o_i}\right| \times 100, \tag{4}$$

$$R^2 = 1 - \frac{\sum (t_i - o_i)^2}{\sum (o_i - \bar{o})^2} \tag{5}$$

where t is the target value, o is the output, $\bar{o}$ is the mean of the output, and n is the number of samples.

In this study, three different ANN models are developed. The difference of models depends on the input neuron numbers. The output parameter for all models is fixed as a BDI value. Figure 3 illustrates the structures of three different ANN models.



(a) First ANN model

(b) Second ANN model

(c) Third ANN model

Figure 3. The three proposed ANN structures for BDI forecasting.

In the first model, the past observation value of the BDI (BDI_{t-1}) is used as an input parameter. In the second model, the last two observation values of the BDI (BDI_{t-1} and BDI_{t-2}) are selected for input parameters. In the last model, COP is added to the input parameter. That is, the last model has two neurons, the previous observation of the BDI and the COP (BDI_{t-1} and COP_{t-1}).

3. Results and discussion

3.1. First model

Table 1 shows the MAPE and R^2 values of the training, validation, and test data sets for each different number of hidden neurons. As shown in Table 1, the minimum error is found when 8 hidden nodes exist. MAPEs are obtained as 6.5755, 11.0962, and 5.7895 while R^2 values are computed as 0.9689, 0.9249, and 0.8545 for training, validation, and test data sets respectively.

Table 1. Performance of the first model for different numbers of hidden neurons.

Number of hidden neurons	MAPE			R^2		
	Train	Validation	Test	Train	Validation	Test
1	6.761477541	10.4371824	5.7794703	0.966717	0.927845	0.852718
2	7.209047979	8.13390634	6.1621093	0.958934	0.946242	0.821599
3	6.712943835	11.085023	5.7862664	0.967741	0.924595	0.850316
4	6.706753898	10.122032	5.7774109	0.967792	0.929886	0.854044
5	6.699393609	10.1204659	5.7984848	0.967815	0.929754	0.853997
6	6.670058304	12.1117473	5.8153819	0.967939	0.918153	0.852484
7	6.610876735	11.9091013	5.8124784	0.968555	0.919693	0.852558
8	6.575501844	11.0962036	5.7895984	0.968963	0.924976	0.854546
9	6.682400281	14.0241844	5.8044624	0.968219	0.901011	0.852586
10	6.799971947	13.7597326	6.3363637	0.966758	0.882482	0.84258
11	6.570973854	17.7985418	5.9093989	0.969837	0.857595	0.84812
12	6.510932312	14.5954618	5.8916111	0.970726	0.895932	0.849033
13	6.738600017	11.2579706	6.2606623	0.968761	0.910843	0.829804
14	6.810129039	9.88864985	5.8624945	0.968096	0.922197	0.85437
15	6.877108115	9.91639792	6.0514788	0.967745	0.922096	0.861813

The regression graphic between the estimated ANN values and actual BDI data is shown in Figure 4. The correlation coefficients are obtained as 0.9843, 0.9728, 0.9259, and 0.9861 for training, validation, test, and all data sets respectively. Figure 5 shows the BDI forecasts of the ANN and actual values of the BDI for 2010–2016. As it is clearly seen in Figure 5, the prediction of the first ANN model was reasonably consistent with the real BDI values.

3.2. Second model

Table 2 gives the MAPE and R^2 values of the training, validation, and test data sets for different hidden neurons. It can be observed from Table 2 that the minimum error is found when the numbers of hidden nodes are chosen as 12. MAPEs are obtained as 5.3897, 7.5889, and 6.3738 while R^2 values are obtained as 0.9829, 0.9397, and 0.8352 for training, validation, and test data sets, respectively.

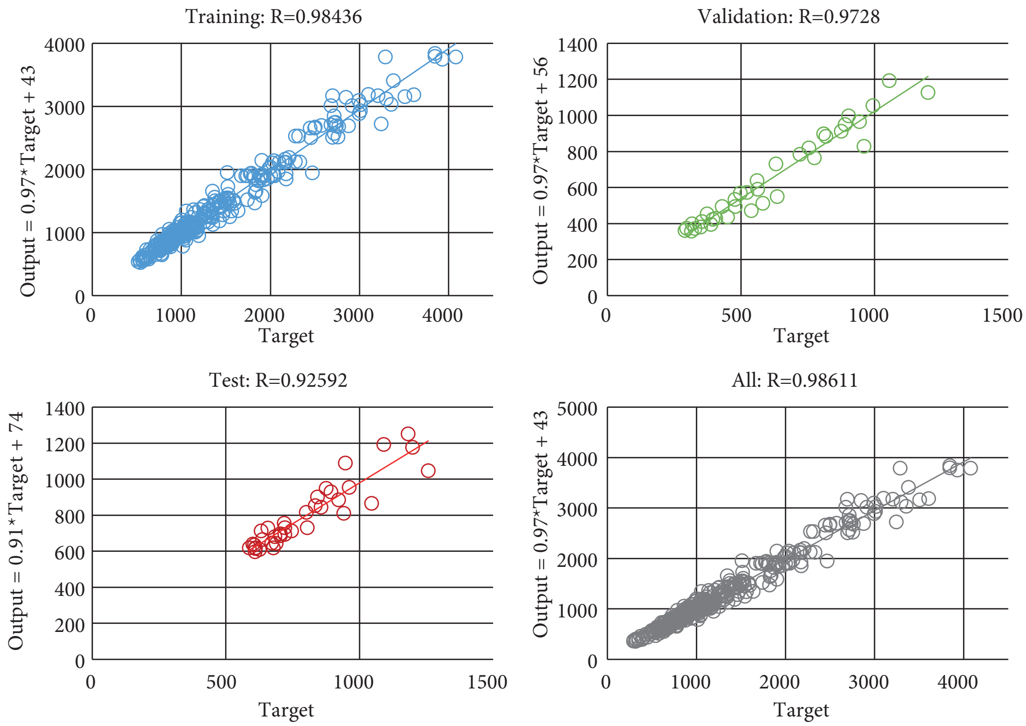


Figure 4. Regression graphics of the first optimum network.

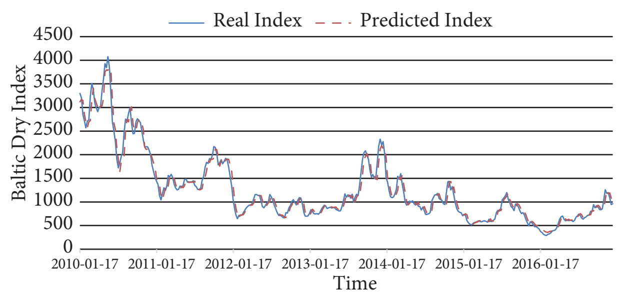


Figure 5. Comparison of actual and predicted values of BDI for first model.

The regression graphic between the estimated ANN values and actual BDI data is shown in Figure 6. The correlation coefficients are obtained as 0.9914, 0.9747, 0.9228, and 0.9920 for training, validation, test, and all data sets respectively. These results indicate that the actual and the predicted values are consistent with each other.

The BDI forecasts of the ANN and actual values of the BDI for 2010–2016 are plotted in Figure 7. Compared with the first model, the second model is more suitable in forecasting because the last two observational values of the BDI are taken into account.

3.3. Third model

Table 3 gives the MAPE and R^2 values of the training, validation, and test data sets for different hidden neurons. The minimum error is found when the numbers of hidden nodes are chosen as 14. MAPEs are obtained as 5.9050, 9.0803, and 6.7417 while R^2 values are obtained as 0.9802, 0.9214, and 0.8137 for training, validation, and test data sets, respectively.

Table 2. Performance of the second model for different numbers of hidden neurons.

Number of hidden neurons	MAPE			R^2		
	Train	Validation	Test	Train	Validation	Test
1	5.814721	7.596328	6.570161	0.979407	0.941549	0.974679
2	5.858691	7.498012	6.626781	0.97976	0.943062	0.974475
3	5.805107	7.430383	6.503628	0.979935	0.943982	0.975524
4	5.774512	7.415653	6.519436	0.979975	0.944484	0.975126
5	5.926224	7.604046	6.461248	0.979786	0.940189	0.975988
6	5.804397	7.617727	6.49227	0.978367	0.941562	0.975863
7	5.928589	7.567298	6.277098	0.980403	0.940243	0.976244
8	5.737645	7.590232	6.362035	0.980454	0.941124	0.97583
9	5.524206	7.666587	6.628703	0.982038	0.938995	0.973141
10	5.653778	7.589406	6.614576	0.982263	0.940949	0.962233
11	5.450625	7.537558	6.07026	0.981668	0.940138	0.851934
12	5.389707	7.588978	6.373863	0.98294	0.939743	0.835289
13	5.547646	7.768788	6.3726	0.983194	0.937395	0.980118
14	5.484591	7.991719	6.665152	0.982882	0.935986	0.970027
15	5.333988	7.703078	6.706736	0.984192	0.939437	0.963715

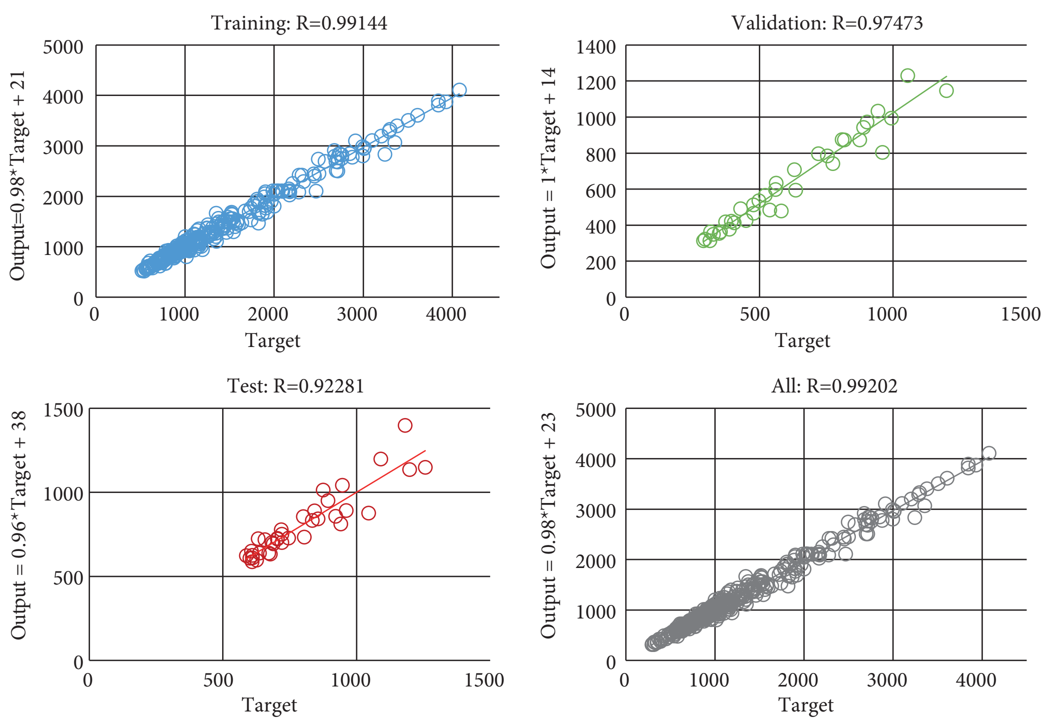


Figure 6. Regression graphics of the second optimum network.

The regression graphic between the estimated ANN values and actual BDI data is shown in Figure 8. The correlation coefficients are obtained as 0.9900, 0.9716, 0.92713, and 0.9907 for training, validation, test, and all data sets, respectively. These results indicate that the actual values and the predicted values are consistent with

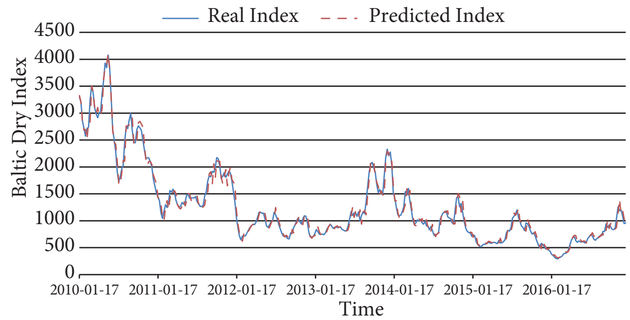


Figure 7. Comparison of actual and predicted values of BDI for second model.

Table 3. Performance of the third model for different numbers of hidden neurons.

Number of hidden neurons	MAPE			R^2		
	Train	Validation	Test	Train	Validation	Test
1	6.74264	9.368313	5.695977	0.966748	0.938217	0.84913
2	6.712282	8.521854	5.796066	0.966876	0.939309	0.84677
3	6.67628	7.179932	5.956284	0.96968	0.949186	0.830884
4	6.572029	13.81083	6.154935	0.969229	0.894697	0.823138
5	6.691252	7.854163	6.415554	0.96812	0.945966	0.793224
6	7.723903	7.615477	6.543447	0.965099	0.937447	0.789845
7	7.028973	7.618755	6.735071	0.968792	0.932365	0.754348
8	6.546412	9.637368	6.023467	0.969382	0.923863	0.836217
9	6.304975	8.552965	5.840164	0.973406	0.932011	0.863408
10	6.553326	10.54512	8.465764	0.970224	0.917609	0.742217
11	6.373009	6.993421	6.582158	0.975299	0.952787	0.804898
12	6.516528	8.171411	6.212293	0.971262	0.941061	0.815402
13	5.984894	10.95103	8.189331	0.977817	0.915495	0.736951
14	5.905083	9.08031	6.741771	0.980223	0.921499	0.813732
15	5.737717	11.71945	10.42678	0.98019	0.869838	0.576905

each other. Figure 9 shows the BDI forecasts of the third model and actual values of the BDI for 2010–2016. In general, the predicted BDI values of the ANN model were acceptably consistent with the real BDI values.

3.4. Comparison of proposed models

In this section, optimum structures of the three different models developed in this paper are compared to each other. Optimum structures for the first, second, and third models are obtained as 1-8-1, 2-12-1, and 2-14-1, respectively. In order to compare these models based on MAPE and R^2, the weighted arithmetic mean (WAM) is calculated by using Eq. (6) as given in Table 4:

$$WAM = \frac{\sum x_d \times n_d}{\sum n_d} \tag{6}$$

where d = 1:3 (training, validation and test), n represents number of data for any d, and x is MAPE or R^2 values for any d.

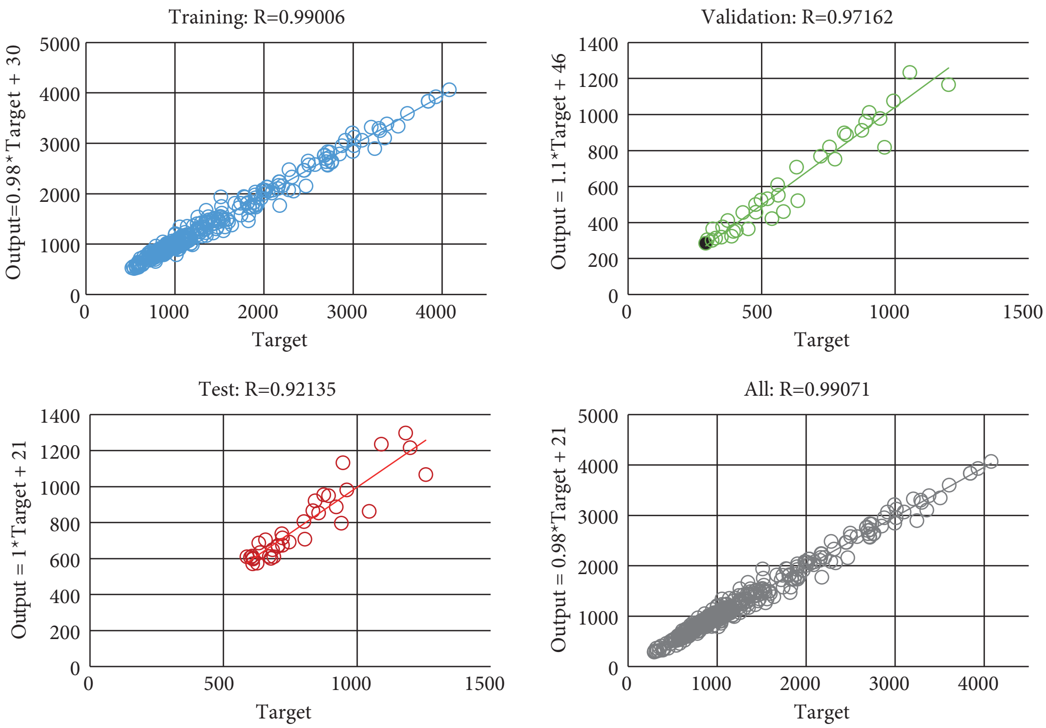


Figure 8. Regression graphics of the third optimum network.

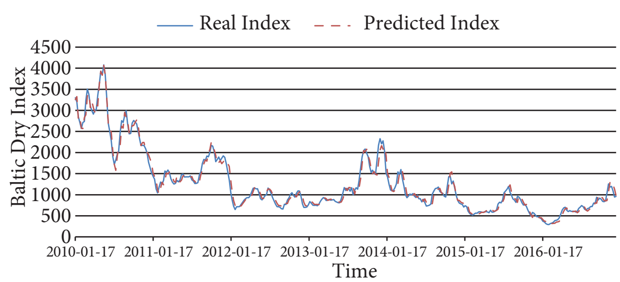


Figure 9. Comparison of actual and predicted values of BDI for third model.

Table 4. Performance analysis of three developed networks.

Model number	ANN structure	MAPE			
		Train	Validation	Test	WAM
1	1-8-1	6.575502	11.0962	5.789598	6.948982
2	2-12-1	5.389707	7.588978	6.373863	5.70805
3	2-14-1	5.905083	9.08031	6.741771	6.306274
Model number	ANN structure	R^2			
		Train	Validation	Test	WAM
1	1-8-1	0.968963	0.924976	0.854546	0.953122
2	2-12-1	0.98294	0.939743	0.835289	0.963855
3	2-14-1	0.980223	0.921499	0.813732	0.957701

As seen in Table 4, the second model has the minimum value of MAPE and the maximum value of R^2. The third and first models follow, respectively. The probable reason underlying the third model's more consistent results might be using the BDI and COP simultaneously as input parameters. COP is not considered in the other models; thus, they have relatively high error rates.

Number of inputs might be increased in order to minimize error rates (MAPE) in BDI forecasting. However, using three or more weekly BDI values will increase network complexity. In the proposed study, the two last weekly values of BDI and COP are used. In that way, a model is generated with high accuracy by using minimum inputs.

4. Conclusions

Maritime transportation plays a locomotive role in the global trade system and world economy. Due to 90% of commodities being carried by ocean-going ships, maritime statistics open a window to global economic actions. The BDI is the principal indicator for shipping prices of bulk cargoes that is generated from daily reported fixtures or estimations of the Baltic Exchange.

It is generally hard to forecast the BDI because it is volatile, complex, and cyclic. In the shipping sector, ship owners, ship brokers, operators, traders, etc. generally depend on their past experience for their future decisions. Previous studies generally investigate BDI forecasting by considering diverse statistical regression methods. The present paper was prepared to be the first to indicate the compatibility and usability of the ANN method for BDI forecasting. In this study we first introduced BDI forecasting by using solely an ANN method. Then we added COP as an input parameter. Three different models were set using the real data from January 2010 to December 2016 and their regression graphics and performances were presented.

Comparing the second model using the last two observational values to the first model using the last observational values, the second model is found more suitable in forecasting the BDI. Comparing the second and third models, it is found that COP has a slightly lower effect on BDI forecasting. The main reason underlying this result might be the fluctuations of the crude oil prices because of high dependence on global effects such as economic crises, wars, etc. Our detailed investigations reveal that the second model is the best one for BDI forecasting with MAPEs of 5.389707, 7.588978, and 6.373863 for training, validation, and test data sets, respectively. The WAM of these values is 5.70805. R^2 values of the second model are obtained as 0.98294, 0.939743, and 0.835289 for training, validation, and test data sets, respectively. R^2 of all data is 0.963855. The performance results indicate that the models proposed in this study fit well for BDI forecasting. Finally, this study validates the effectiveness of ANNs for modeling and forecasting the BDI and demonstrates the applicability.

As the BDI is generated by considering fixtures that are signed between the charterers and owners, and predictions derived from the real cases, all issues related to the BDI will benefit practitioners in the business sector. Governments, maritime economists, investors, ship owners, charterers, academicians, brokers, etc. will always need such statistics regarding BDI forecasting in order to set a vision. A forecasting model is required not only for the present time but also the future for long-term success and sustainability.

In the future, the proposed models might be tested for other indices such as the Baltic Supramax Index, Baltic Panamax Index, or Baltic Capesize Index. The results might be compared with each other. The applied methods in the literature (fuzzy delphi, fuzzy integrated logical forecasting, multivariate autoregressive models, support vector machine, etc.) and the proposed method might be studied in another comparison research. The proposed models will be applied in the future to check their applicability and usability by comparing the findings and results. In the future, new hybrid BDI forecasting models with updated and long prospected data can be generated. In this study, we used the BDI and COP as input parameters. In the future, input/output parameters might be diversified and the number of inputs and outputs might be changed.

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