A FUZZY NEURAL NETWORK MODEL FOR ANALYZING BALTIC DRY INDEX IN THE BULK MARITIME INDUSTRY

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SUMMARY

Baltic Dry Index (BDI) is one of the important indexes in the dry bulk shipping market. BDI analysis and forecasting is one of important activities of shipowners, charterers, shipping carriers, importers and exporters, and banks in the dry bulk shipping market. Based on the accurate BDI analysis and forecasting , the shipowners, charterers, shipping carriers, importers and exporters, and banks in the bulk shipping market could make many important decisions of shipping operation, management and financial invest such as building a new bulk carrier, chartering-in or chartering-out a second-hand bulk carrier, demolishing an old bulk carrier, and providing funding for shipowners. Thus, this paper adopts a fuzzy neural network model to analyze the relationship between the BDI in the international bulk shipping market and the major economic indexes in the global financial market. Finally, the proposed fuzzy neural network model is tested by empirical data during the period of 2000-2015. The results show that the fuzzy neural network model has high accuracy of forecasting. The fuzzy neural network model in this study seems to be promising and the model could help the shipowners, charterers, shipping carriers, importers and exporters, and banks forecast future BDI points in the bulk shipping market, and then make important decisions and operation strategies of shipping operation, management and financial invest.

1. INTRODUCTION

Generally, the types of seaborne trade cargoes include (a) dry cargo trade: major and minor dry bulks, (b) tanker trade, and (c) containerized trade. Major dry bulk cargoes are iron ore, coal, grain, bauxite, alumina, and phosphate rock. Minor dry bulk cargoes are agribulks, metals and minerals, and manufactures. Tanker trade cargoes are crude oil, refined petroleum products, liquefied natural gas (LNG), and liquefied petroleum gas (LPG). According to UNCTAD (2015), the structure of international seaborne trade is: iron ore (13%), coal (12%), other dry (9%), minor bulks (15%), grain (4), crude oil (17%), petroleum products (9%), gas and chemicals (6%), and containerized cargo (15%). It is noted that most seaborne trade cargoes are major dry bulks and the dry bulk shipping market is one of the most important shipping markets.

Forecasting is one of crucial planning and developing strategies activities for the future challenges in various industries and markets, especially in the international dry bulk shipping market. The accurate Baltic Dry Index (BDI) forecasting can contribute to understanding and avoiding the uncertain risk of the finance and freight rates in dry bulk shipping market. Baltic Dry Index which is an economic indicator in the international bulk shipping market, issued daily by the London Baltic Exchange. BDI provides an evaluation of the freight rates of major bulk cargoes transported by major bulk carriers. The major bulk carriers include: Handysize, Supramax, Panamax, and Capesize vessels. Based on the accurate BDI forecasting, the shipping carriers, shipowners and charterers, importers and exporters, and banks in the bulk shipping industry can make a right decision for reducing the transportation costs and financial risks, avoiding the financial lost, and increasing freight rate earnings. It is very difficult to forecast accurately BDI because some specific characteristics exist in the dry bulk shipping market. These specific characteristics include the seasonal and cyclical fluctuation of the supply and demand of vessel capacities, the non-stationary, non-linear, and highly fluctuation nature of freight rate, and the uncertainty of international political and economic situations.

In most economic markets, the supply and the demand will decide the prices. Similarly, the supply of vessel capacity and the demand for bulk cargo transportation will decide the freight rates in the international bulk shipping market. BDI is an important index for measuring the demand for dry bulk cargo transportation and the supply of vessel capacities. Basically, the bulk shipping freight rate and the BDI points will rise when the demand for bulk cargo transportation is larger than the supply of vessel capacities. On the contrary, the bulk shipping freight rate and the BDI points will drop when the supply is larger than the demand. In addition to taking account of the uncertainty of international political and economic situations, the dry bulk shipping market would become more complex and the freight rates would become non-stationary and non-linear. Thus, it is more difficult to forecast accurately BDI points.

In the past, scholars have introduced and presented some forecast techniques such as moving average (MA), auto regression (AR), and smoothing methods for analyzing and forecasting the BDI points in the dry bulk shipping industry. These methods are able to predict a particular type of data accurately, but they are inappropriate for some time series forecast problems in the real world (Duru, 2010). The conventional forecast methods require normality and stationary. However, a lot of data in the bulk shipping market are usually not stationary. Therefore, fuzzy sets theory which was initially introduced by Zadeh (1965) is an appropriate forecast approach to deal with the non-stationary problem in the bulk shipping market. In addition, a fuzzy-based forecast method does not require a large stationary data sample, or a purely quantitative data.

Based on the above-mentioned characteristics in the dry bulk shipping market, i.e. the seasonal and cyclical fluctuation of the supply and demand of vessel capacities, the non-stationary, non-linear, and highly fluctuation nature of freight rate, and the uncertainty of international political and economic situations, the fuzzy neural network approach is an approach to analyze the relationship between BDI in the international dry bulk shipping market and the major economic indexes in the global financial market. Although fuzzy neural network has been widely applied to various forecast problems with seasonal or cyclical fluctuation, non-stationary, non-linear nature, or uncertainty in the past, few studies focused on BDI forecasting in the bulk shipping market by combining fuzzy theory and neural network. Therefore, this study combined both fuzzy theory and neural network to analyze BDI in the maritime industry.

The rest of this paper is organized as follows. Section 2 is the literature review. The previous studies on the bulk shipping and fuzzy neural network are reviewed. Methodologies including fuzzy sets theory and neural network are introduced in section 3. An empirical study is shown in section 4, followed by the conclusions in section 5.

2. LITERATURE REVIEW

2.1 BULK SHIPPING

Some financial methodologies have been applied to analyze the dry bulk shipping market. Cullinane (1995) used a Markowitz portfolio selection methodology as a tool for avoiding uncertain risk in the bulk shipping industry. Han *et al*. (2016) introduced an integrated approach for identifying, quantifying and avoiding most financial risks in the dry bulk shipping industry. The integrated approach combines the autoregressive conditional heteroskedasticity model, historical data distribution goodness-of-fit test and Monte Carlo simulation.

Various regression analysis approaches have been used to analyze and forecast the shipping industries. Chou *et al*. (2008) proposed a modified regression model for forecasting the volumes of import/export containers. The results show that the modified regression has better performance of forecasting. Chou and Lin (2010) developed a vector AR model for analyzing the relationship between Baltic Dry Index and steel price index. The results show that the accuracy rate of forecasting fell in a reasonable interval. By using AR-GARCH and GMM regression, Xu *et al*. (2011) studied the relationship between the dry bulk freight rates and the supply of vessel capacities in the dry bulk shipping market. The results reveal that the fleet size growth positively affects the freight rate.

Some researchers applied fuzzy approach to analyze and forecasting BDI. Duru (2010) developed an improved fuzzy time series approach for forecasting the BDI in the dry bulk shipping market. Empirical studies show that the improved fuzzy time series approach is the better one than those conventional benchmark methods. Duru (2012) proposed a fuzzy time series model with multivariate inference to forecast the dry cargo freight in the bulk shipping market. The results show that the improved fuzzy time series model with multivariate inference has better accuracy of forecasting.

Other useful methodologies also have been applied to analyze and forecast the nature of shipping market. Wang *et at*. (2013) introduced an improved system dynamics model to forecast the volume of containers in the international shipping market. The results show that the improved forecasting model has better forecasting performance than those of other forecasting approaches. Kavussanos and Alizadeh (2001) adopt statistic method to explore the nature of seasonality across freight rates of various types of vessels, contract and market conditions. Zeng and Qu (2014) analyzed the volatility of BDI in the dry bulk shipping market by using empirical mode decomposition (EMD). The numerical experiments show that the EMD model can effectively reveal the characteristics of dry bulk freight rates.

2.2 FUZZY NEURAL NETWORK

Mendel (1995) presented a fuzzy logic system which combined linear, non-linear functions and neural networks. Chou *et al*. (1996) introduced a neural networks stock trading decision support system and applied to forecasting the TSEWPI (Taiwan Stock Exchange Weighted Price Index). The results show that the neural networks stock trading decision-making system seems to be promising. Chen *et al*. (2013) presented a fuzzy neural network method for forecasting the solar radiation at different weather conditions. The results show that the fuzzy neural network has better accuracy performance than other solar radiation forecasting methods. He *et al*. (2014) developed an artificial neural network model and a neuro fuzzy inference model for forecasting river flow in the semiarid mountain region. The results show that the artificial neural network model and the neuro fuzzy inference model can be successfully applied to forecasting river flow in the semiarid mountain region.

Based on the above literature, it is noted that in the past scholars analyzed and forecasted the BDI by various financial, regression, time series, and fuzzy theory methodologies in section 2.1. In section 2.2, various models combined fuzzy theory and neural network were applied to solving various forecasting problems in various industries and markets such as stock exchange market and environment engineering. Few forecasted BDI in the bulk shipping market by combining fuzzy theory and neural network. Therefore, this study combined both fuzzy theory and neural network to analyze BDI in the maritime industry.

3. METHODOLOGIES

3.1 FUZZY THEORY

Fuzzy sets theory is initially introduced by Zadeh (1965). A fuzzy number is defined as follows. Suppose $A_1=(c_1, a_1, b_1, d_1)$ is a trapezoidal fuzzy number. The membership function of A_1 is shown as follow.

$$f_{A1}(x) = \begin{cases} \dfrac{(x-c_1)}{(a_1-c_1)}, & c_1 \le x \le a_1 \\ 1, & a_1 \le x \le b_1 \\ \dfrac{(x-d_1)}{(b_1-d_1)}, & b_1 \le x \le d_1 \\ 0, & otherwise \end{cases}$$

The basic arithmetical operations are listed as follows. Suppose $A_1=(c_1, a_1, b_1, d_1)$ and $A_2=(c_2, a_2, b_2, d_2)$ are two trapezoidal fuzzy numbers.

(a) Addition operation on A_1 and A_2
$A_1 \oplus A_2=(c_1+c_2, a_1+a_2, b_1+b_2, d_1+d_2)$
(b) Subtraction operation on A_1 and A_2
$A_1 \Theta A_2=(c_1-d_2, a_1-b_2, b_1-a_2, d_1-c_2)$
(c) Multiplication operation on A_1 and r
$r \otimes A_1= (rc_1, ra_1, rb_1, rd_1)$
(d) Division operation on A_1 and r
$A_1 / r= (c_1/r, a_1/r, b_1/r, d_1/r)$

Fuzzy sets theory has been widely applied to many fields such as fuzzy possibility (Zadeh, 1978). The fuzzy reasoning-based approach to risk analysis under a linguistic environment was presented (Deng *et al*, 2011). Fuzzy similar measurement approaches also have been developed in the literature (Deng, Jiang & Sadiq, 2011). Lee *et al*. (2014) constructed a fuzzy AHP/DEA model associated with the Malmquist productivity index to evaluate the photovoltaics industry in Taiwan. Liao *et al*. (2015) adopted a fuzzy quality function deployment model for improving the management and operational success of the third party logistics industry in Taiwan. Lazakis and Ölçer (2016) applied fuzzy multiple criteria decision making to the selection of maintenance approaches in the maritime industry.

3.2 NEURAL NETWORK

Generally, a basic neural network consists of three layers including input layer, hidden layer and output layer (Chen *et al*., 2013). The definitions and equations of the neural network are shown as follows.

$$h_j = f_1(\sum_{i=1}^{n} v_{ij}x_i + \theta_j) \qquad \text{Eq.(1)}$$

h_j is the value of the hidden layer neuron;
$f_1(\bullet)$ is the tangent sigmoid transfer function;
x_i is the value of the input layer neuron;
v_{ij} is the adjustable weight between the input and hidden layers;
θ_j is the bias of the hidden layer neuron.

$$o_j = f_2(\sum_{i=1}^{n} w_{ij}h_i + r_j) \qquad \text{Eq.(2)}$$

o_j is the value of the output layer neuron;
$f_2(\bullet)$ is a linear transfer function;
w_{ij} is the adjustable weight between the output and hidden layers;
r_j is the bias of the output layer neuron.

A basic fuzzy neural network consists of five layers including input linguistic layer, input term layer, rule layer, output term layer and output linguistic layer (Lin and Lee, 1996). Yager (1992) introduced the concept of fuzzy neural network and its application to the fuzzy logic control system. Fuzzy neural network has been widely applied to a lot of system engineering. Schöneburg (1990) presented a neural network approach for stock price predicting. Kosaka *et al*. (1991) also proposed fuzzy neural network model and its application to securities trading decision support system. Jang (1993) developed an architecture and learning procedure underlying adaptive-network-based fuzzy inference system (ANFIS). The proposed ANFIS is tested by a simulation. The results show that the ANFIS model has better performance than other artificial neural networks and earlier works on fuzzy modeling. Moreira and Soares (2012) introduced a neural network to simulating manoeuvring. It is an alternative to conventional methods of developing manoeuvring mathematical models.

4. EMPIRICAL STUDY

This study collected the BDI data during the period of 2000-2015. The source of BDI data is the Baltic Exchange. The size of BDI data during the period of 2000-2015 is large. Therefore the study just showed part of them in Table 1. The other economic data including: global energy stock index, international metal price index, global agriculture stock index, OECD combined leading index, and US dollar index, are also collected during the period of 2000-2015 shown in Table 1. Actually, this study collected a lot of international major economic indexes, not only the above-mentioned five economic indexes (global energy stock index, international metal price index, global agriculture stock index, OECD combined leading index, and US dollar index), but also other important global economic indexes. After pre-test, the results show that the fuzzy neural network model has better forecasting performance by inputting the above-mentioned five economic indexes. All the collected data are inputted into the fuzzy neural network model. A part of results is shown in Table 2. The whole results are illustrated in Figure 1. Finally, the Root Mean Square Percentage Error (RMSPE) is applied to evaluating the accuracy rate for the fuzzy neural network model. The RMSPE is calculated as follows.

RMSPE=

$$\sqrt{\frac{1}{183}\times(\frac{(1371-1507)^2}{1371}+\frac{(1405-1665)^2}{1405}+...+\frac{(576-293)^2}{576})}\times 100$$

=24.76%

Usually, the forecast accuracy is very high if the RMSPE is less than 10%. The forecast accuracy is good when RMSPE is between 10%-20%. The forecast accuracy is reasonable when RMSPE is between 20%-50%, and the forecast accuracy is low when RMSPE is larger than 50%. The value of RMSPE is 24.76% in this paper. This means the proposed fuzzy neural network forecast model is a reasonable forecast one.

The values of RMSPE in previous most studies are larger than 24.76%. Therefore the results show that this fuzzy neural network model (RMSPE=24.76%) has better forecasting performance than those of other forecasting approaches in previous literature.

Figure 1 illustrates that the forecasted BDI is basically to match the actual BDI in the dry bulk shipping market. This results show that the fuzzy neural network method and selected economic indexes are basically appropriate for forecasting BDI. In 2004, the BDI in the bulk shipping market fluctuated dramatically. As a result, the proposed fuzzy neural network produces lower forecast accuracy in 2004. It is also noted that the fuzzy neural network model produces higher forecast accuracy in some periods, especially in recession periods (2001-2002) and in upward trend periods (2006-2008). On the contrary, the fuzzy neural network model produces lower forecast accuracy in some periods, especially in declining trend periods (2003-2005).

5. CONCLUSIONS

BDI analysis is one of important activities in the international bulk shipping market. In the past, some BDI analysis approaches have been proposed. Few analyzed the BDI by using fuzzy neural network model. Therefore, in order to fill the gap in the previous literature, this paper adopts fuzzy neural network model to analyze the relationship between BDI and major global economic indexes. The results show that the proposed fuzzy neural network model seems to be promising.

In the future work, various forecasting methodologies would be applied to the analysis of the relationship between BDI and economic indexes. Furthermore, some modified fuzzy neural network models or integrated fuzzy neural network approaches will be introduced.

6. ACKNOWLEDGEMENTS

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APPENDICIES

Table 1: BDI and major economic indexes

Year/Month	Global energy stock index	International metal price index	Global agriculture stock index	OECD combined leading index	US dollar index	BDI
2000/01	947.67	65.72	912.71	101.309	101.76	1371
2000/02	928.51	65.86	805.49	101.342	104.69	1405
2000/03	1051.43	63.91	842.34	101.335	105.38	1620
2000/04	1037.13	60.82	783.57	101.294	106.13	1666
2000/05	1119.09	61.98	760.94	101.221	110.56	1602
2000/06	1098.42	61.14	733.31	101.118	106.88	1588
2000/07	1061.89	62.53	719.74	100.986	108.70	1618
2000/08	1141.37	62.34	722.98	100.833	110.51	1639
2000/09	1095.04	65.10	657.51	100.650	115.94	1711
2000/10	1034.26	61.37	657.74	100.430	116.39	1734
2000/11	991.02	59.72	634.27	100.173	116.35	1722
2000/12	1081.46	61.90	686.45	99.892	112.90	1609
2001/01	1052.20	62.30	708.94	99.620	109.97	1566
2001/02	1022.32	61.64	727.62	99.384	113.20	1479
2001/03	997.62	59.35	676.18	99.198	111.28	1502
2001/04	1082.53	58.56	764.06	99.056	116.18	1440
2001/05	1062.10	59.99	760.22	98.949	116.79	1451
2001/06	967.52	57.51	708.04	98.854	118.89	1379
2001/07	957.22	55.16	659.56	98.764	119.30	1222
2001/08	935.46	53.53	665.18	98.679	113.19	979
2001/09	849.09	52.13	556.44	98.620	112.01	945
2001/10	896.06	50.32	591.91	98.634	113.92	898
2001/11	849.35	52.07	659.40	98.739	116.51	855
2001/12	897.60	52.67	672.52	98.922	114.93	870
2002/01	867.35	53.94	704.09	99.148	117.29	931
2002/02	907.45	54.15	736.86	99.375	118.60	960
2002/03	980.34	55.74	760.68	99.557	117.22	1065
2002/04	951.36	55.16	768.24	99.655	117.77	1080
2002/05	937.92	54.43	816.90	99.655	114.12	1032
2002/06	912.57	55.34	814.20	99.569	110.85	1000
2002/07	800.65	54.63	690.73	99.428	104.67	989

Table 1: BDI and major economic indexes (continued)

Year/Month	Global energy stock index	International metal price index	Global agriculture stock index	OECD combined leading index	US dollar index	BDI
2013/04	2097.26	183.55	1794.94	99.938	82.42	876
2013/05	2095.06	176.40	1777.38	100.011	83.83	851
2013/06	1980.45	169.66	1561.91	100.090	80.79	940
2013/07	2165.13	172.66	1753.58	100.175	83.04	1123
2013/08	2134.72	180.90	1807.01	100.264	81.18	1096
2013/09	2235.08	177.88	1927.95	100.350	81.30	1702
2013/10	2305.44	179.02	1990.94	100.425	80.48	1883
2013/11	2301.47	177.96	1920.37	100.480	80.85	1559
2013/12	2278.88	179.33	1962.63	100.502	80.07	2178
2014/01	2187.34	176.39	1876.75	100.501	81.03	1505
2014/02	2273.40	171.96	1958.62	100.494	80.14	1140
2014/03	2239.76	165.02	1866.26	100.493	79.39	1484
2014/04	2375.10	169.51	1950.27	100.490	79.80	1037
2014/05	2448.88	164.52	1967.44	100.480	80.00	991
2014/06	2578.35	161.85	1974.46	100.465	80.47	910
2014/07	2551.20	168.79	2107.68	100.442	80.39	796
2014/08	2490.95	168.17	2048.82	100.350	81.42	937
2014/09	2367.83	161.45	1915.33	100.386	84.26	1121
2014/10	2120.36	156.83	1742.86	100.381	85.15	1013
2014/11	2186.95	156.42	1755.67	100.321	87.93	1317
2014/12	1958.74	148.73	1568.60	100.308	88.46	910
2015/01	1900.21	140.31	1482.72	100.306	92.35	723
2015/02	1940.86	137.27	1590.24	100.290	94.20	542
2015/03	1867.43	134.60	1520.59	100.105	99.60	576

Table 2: BDI forecast by fuzzy neural network

Year/Month	BDI forecast by fuzzy neural network	Actual BDI	Actual BDI up or down	Forecasted BDI up or down	Accuracy
2000/01	1507	1371	Up	Up	True
2000/02	1665	1405	Up	Down	False
2000/03	1656	1620	Up	Down	False
2000/04	1578	1666	Down	Up	False
2000/05	1641	1602	Down	Down	True
2000/06	1416	1588	Up	Up	True
2000/07	1502	1618	Up	Down	False
2000/08	1290	1639	Up	Up	True
2000/09	1669	1711	Up	Down	False
2000/10	1635	1734	Down	Up	False
2000/11	1669	1722	Down	Down	True
2000/12	1368	1609	Down	Up	False
2001/01	1450	1566	Down	Down	True
2001/02	1434	1479	Up	Down	False
2001/03	1350	1502	Down	Down	True
2001/04	878	1440	Up	Up	True
2001/05	1051	1451	Down	Up	False
2001/06	1148	1379	Down	Down	True
2001/07	1055	1222	Down	Up	False
2001/08	1193	979	Down	Up	False
2001/09	1284	945	Down	Down	True
2001/10	1062	898	Down	Down	True
2001/11	1019	855	Up	Down	False
2001/12	965	870	Up	Up	True
2002/01	1058	931	Up	Up	True
2002/02	1059	960	Up	Up	True
2002/03	1091	1065	Up	Up	True
2002/04	1154	1080	Down	Down	True
2002/05	1038	1032	Down	Up	False
2002/06	1109	1000	Down	Up	False
2002/07	1385	989	Up	Down	False

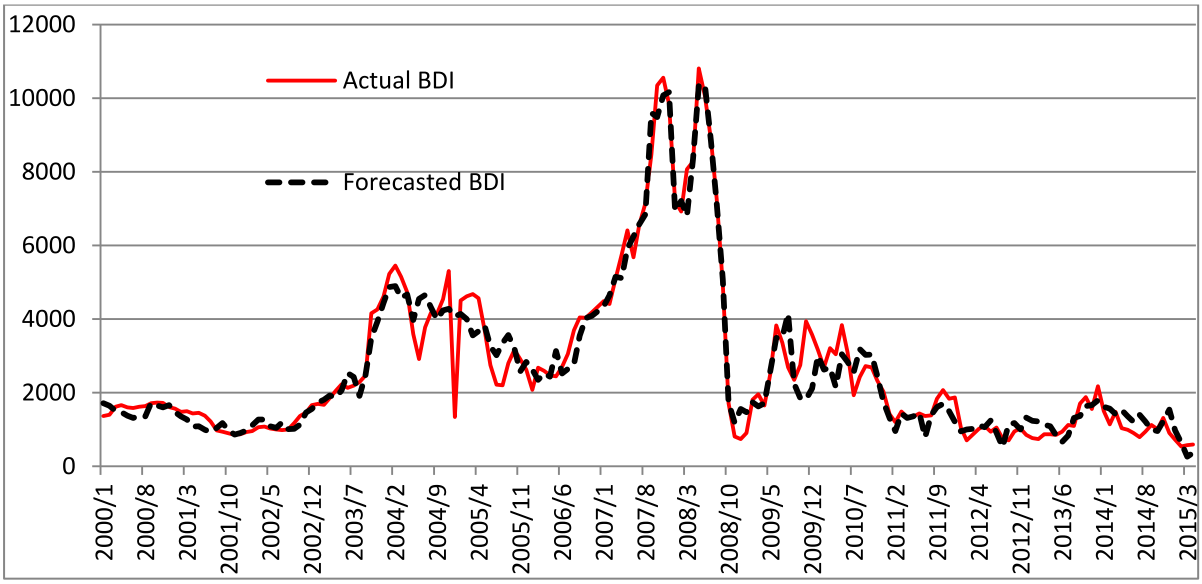

Figure 1: A comparison between actual BDI and forecasted BDI

