Bulk Carrier Market Prediction using Artificial Neural Network

Prof. Dr. Taymoor Nazmy
Ex-vice Dean of Computer Science
Faculty of Computer &I.S.,
Ain Shams University
Tel:+2 012 456 6170
Mail:ntaymoor19600@gmail.com

Mohammed Rizk Awad
Computer Science Dept.,
Faculty of Computers & I.S.
Ain Shams University
Tel:+2 010 344 6105
Mail:mrezk@nnc.com.eg

Prof. Dr. Ismael Amr Ismael
Dean of Faculty of Computer
&Information Sciences,
Misr International University
Tel:+2 010 447 1033
Mail:amr444_2@hotmail.com

Abstract

Everyday the ship-owners use his commercial judgment to interpret shipbuilding market information in a way that will best profit his company. Investors are waiting for the best times to build ships, and this is a critical decision for the investors in this field, this decision is depending on many variables. However, the intense competition in the world shipbuilding market results a volatile pattern of shipbuilding prices. In this paper, we will concentrate one type of vessel, the dry-cargo bulk carrier, and attempted to uncover the benefit of using artificial neural network (ANNs) in forecasting the order book for bulk carrier shipbuilding. The artificial neural network was used for forecasting, the required database for a well-trained network is big enough in comparison to other forecasting methods. Finally, it will constitute a radical tool for decision making for financial institutions as well as a strategic tool that may give answers to ship-owners. Our model is tested for year 2011, and we make the comparison of the real and production data for year 2011 with satisfaction error. We apply our model for prediction the Bulk carrier order book for year 2012.

Keywords: Artificial Neural Network, Supply/demand analysis of Shipbuilding Market.

1. INTRODUCTION

Development in the shipping industry, including all its fields and activities during the past years of the last century lead to the maximization of its role in serving the world trade, and the international trade played an influential role in the progress and growth in the shipping industry. Countries paid more attention to this industry as it deserves, it is considered one of the most important pillars of economy affecting foreign trade.

The complexity of this industry and its dependence on world economic conditions require a wealth of knowledge and skills in order to cope with day-to-day operations and events that keep routine away. This complexity and skills requirement make ship-owners some of the most respected investors in the world that can flourish in almost anything they do besides shipping [1].

Commercial fleet considered one of the elements of the shipping industry and it reflects its development. The commercial fleets became an important link in the chain of this industry due to its development, complexity and multiplicity of its activities, and through which foreign trade at the local and global levels are deliberated. Any marine company follow a general development strategy in order to support its fleet in terms of quality and payloads to cope with demand of trade nowadays and in the future, it also must cope with the evolution of technology in the shipbuilding industry and the constraints imposed by the international bodies which is the basis for the implementation of a central policy replacement and renovation of its fleet within the available liquidity of the company in addition to the funding opportunities available from banks in order to achieve optimal continue.

Merchant ships are large and expensive item of capital equipment in a world, someone has to decide when to order new ships and when to scrap old ones. If ships are not built but trade grows, eventually business will halt. However, if ships are built and trade does not grow, it is a very different story, with no cargo, the expensive ships sit idle while the unfortunate investors watch their investment rust away [2].We will concentrate on one type of vessel, the dry cargo bulk carrier.

Dry cargo Bulk carrier, bulk freighter, or bulker is a merchant ship specially designed to transport unpackaged bulk cargo, such as grains, coal, ore, and cement in its cargo holds. Today, bulkers make up 40% of the world's merchant fleets and range in size from single-hold mini-bulkers to mammoth ore ships able to carry 400,000 metric tons of deadweight (DWT). Deadweight is it the weight of materials inside the ship or it includes self weight of ship + fuel tank + food + crew weight. Major bulk carrier size category is Small, Handsize, Handymax, Panamax, and Capesize bulk carrier.

The better time to make an order for new building ship is a critical decision and it must be an accurate decision, we need to predict Bulk carrier market to support decision making to select the best time to make this critical order.

We briefly present some of the research literature related for prediction bulk carrier market. Voudris [3] is one of researcher that Analyze and Forecast Capesize Bulk Carriers Shipping Market using Artificial Neural Networks. He it is attempted to uncover the benefits of using Artificial Neural Networks (ANNs) in forecasting the Capesize Ore Voyage Rates from Tubarao to Rotterdam with a 145,000 DWT Bulk carrier. This work focuses one type of bulk carrier and one type of goods, using the fright rate as a desired column.

Another work a new method for studying the world ship market is expounded [4]. Economic laws, man-made and subjective factors and philosophy are integrated with fuzzy theory and used to analyze the mechanism of the market. The paper advances fuzzy probability simulation (FPS) theory, and points out that market forecasts (including the price of a new ship) are ‘forecasts with controllable results’. In addition, simulation of the market is carried out, based on FPS theory. We see that we use fuzzy theory when lake of data, but when the data is available we see that artificial neural network is more accurate tool than fuzzy.

Bulk carrier's order book is referred to periodical prices when the new buildings are ordered and recorded and not when the ships are delivered [5]. This element should be taken into serious consideration, since there is an interval of about one year from the order to the delivery. In addition, the data for the order book includes new orders that took place with extremely good contract terms.

We see that Bulk carrier order book is the most oriented variable that determines the best time to build the bulk carrier ship. We gather our variable from Clarkson's tables database, we took an average of some columns like the table of "Dry Bulk Freight Rates for 1 Year time charter US$ per day" it shows handysize, handymax, supramax, panamax and modern capesize, to reach dry bulk freight rates for 1-year time charter per day.

We employee an artificial neural network to forecast bulk carrier order book. The most suitable neural network is Multilayer perceptron. Past and recent scientific papers showed that the use of Multi Layers Perceptron (MLPs) Networks is offering satisfactory results when they are used to forecast time series problems. Neuro Solutions for Excel Software Program are used to build Intelligent Decision Support Systems based on Neural Networks that have been used to predict the value of bulk carrier order book. We take twelve months with a time lag in order book Colum, for example the input for jan 2000 leading to the desired of jan 2001 and so on.

The organization of our work is as follows. (2) Literature survey. (3) Data description. (4) Material and methods (5) Experimental result (6) Conclusion and future work.

2. Literature Survey:

The shipbuilding Market is volatile because of many unseen factors that can influence of it. Economic structure of the Shipbuilding Market is closely linked to the shipbuilding market, the industry work within a quite separate competitive system with the result that events in the Shipbuilding Market do not always mirror those of the shipping market [2].

The supply/ demand analysis of the Shipbuilding Market provides a valuable framework, which interpret the likely effects of market developments.

1. The shipbuilding demand functions:

From the experience, the following four influences can be expected to have particularly important roles to play in explaining the demand function for merchant ship: Shipping freight rates, liquidity, total world fleet, and credit availability.

2. The shipbuilding supply function:

How much capacity will be available to meet demand? As with any market driven by supply and demand, the answer to this question depends on the tradeoff between cost and price. We expect supply to increase with price. However the precise shape of the supply curve at a point in time will depend on three factors Total order book, New building Price and Delivery.

Many researchers claim that the market is dynamic, non-linear, complicated and chaotic in nature. So it is difficult to deal with normal analytical methods like time series analysis. These chaos systems are sensitive to initial conditions. So the neural networks are effective to deal with such a non-linear system.

Recent advances in soft computing led to a new era in the field of financial forecasting. In the most recent times, the soft computing tools based on such as multilayer Artificial Neural Network (ANN) [6],[7], Fuzzy Logic (FL) [8], Genetic Algorithm (GA) [9], have been applied to financial forecasting.

This present paper of our interest is to develop a low complexity and accurate prediction model which is better suited for long term prediction.

3. Data Description

The data were collected from "Clarksons Research Studies" (CRS) [10], which provides a statistical and research service to Clarkson brokers, their clients and the shipping world in general. The following are some examples of Clarkson database:

Table 1: Bulk carrier order book million dwt

Year	Oil and prod tankers1	Spec.tankers2	Small tankers3	tankers rock	Bulkers Bulk	combos ainer	All bulk Dry
1997	19.89	1.94	0.39	22.23	29.52	0.55	52.30
1998	39.8	2.19	0.60	42.59	26.15	0.44	69.18
1999	42.88	2.91	0.44	46.24	23.92	0.44	70.60
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
2010	126.58	12.49	2.60	141.68	303.41	2.88	447.96
	115.97	8.89	2.01	126.87	284.23	1.28	412.38

1 "Oil" covers vessels in the crude oil & oil products sectors >10,000 dwt. Includes tankers with IMO 3 grade specification.
2 "Spec." covers IMO 1&2 chemical tankers and other tankers designed for the carriage of specialist liquids >10,000 dwt.
3 "Small" covers all tankers <10,000 dwt. 4 Tankers over 10,000 dwt before 1996.

Table 1 shows an example of bulk carrier order book for each type of bulk and the total bulk carrier order book by million deadweight.

Table2: Bulk carrier Fleet & Deliveries million dwt

	BULKCARRIER FLEET BY SIZE					BULKCARRIER DELIVERIES BY SIZE				
Year	Over 100	60-100	40-60	10-40	Total fleet	Over 100	60-100	40-60	10-40	Total fleet
1996	74.4	57.3	40.7	81.5	253.8	7.9	3.3	4.2	2.1	17.5
1997	79.0	61.4	43.1	81.4	264.8	7.2	5.5	3.4	2.6	18.7
1998	77.8	62.9	44.9	78.4	264.0	2.1	4.4	3.5		11.8
1999	77.9	65.5	45.1	76.7	266.9	4.2	4.7	2.0		12.6
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2008	143.4	114.7	82.9	76.2	417.2	8.6	6.4	6.4	3.0	24.5
2009	169.9	121.1	91.8	75.4	458.3	21.0	6.9	10.2	4.9	43.0
2010	209.1	136.6	108.9	81.2	535.8	38.4	15.7	17.6	8.2	79.9
2011	241.0	152.7	123.7	86.2	603.6	40.7	22.4	16.8	9.8	89.7

Table2 shows bulk carrier fleet and deliveries by size for each weight category for bulk carrier fleet. five independent variables that were described in table3 are selected, we believed that they hide information for the future shipbuilding total order book, the 5 input variable are (date, total bulk carrier fleet development, total bulk carrier deliveries, weighted average earnings all bulkers, average dry bulk freight rates 1 year time charter, and total dry bulk seaborne trade), and the desired variable is Total order book.

Table 3 also shows the training rows from January 2000 to December 2008 and the test data from January 2009 to December 2009, finally it shows the production rows from January 2010 to December 2010.

Table 3. Input and Desired data from "Clarksons" shipping Economics

(S)month	year	Total Bulk carrier Fleet Development	Total Bulk carrier Deliveries	Weighted Average Earnings All Bulkers $/ day	average dry bulk freight rates 1 year time charter US$ per day	total dry bulk seaborne trade	Bulk carrier Order book	
jan	2000	266.94	2.01	7687	10683.75	3661	35623797	
feb	2000	268.71	0.66	7714	10314.73	3665	33878045	
mar	2000	268.93	1.94	8701	10215.25	3669	32921789	
apr	2000	270.15	1.06	9199	9812.21	3677	30794581	
may	2000	271.1	0.61	9062	9799.32	3685	31218815	
....	....	....	....	....	....	....	....	Training rows
jan	2011	536.05	11.98	10641	18753.24	6033	231839404	
feb	2011	546.84	4.17	9587	18456.34	6036.25	219770607	
mar	2011	549.44	8.16	11875	18159.44	6037.875	213993488	
apr	2011	554.77	6.62	10715	17565.63	6039.5	202987352	
may	2011	559.87	9.03	11005	16971.83	6042.75	194041559	
jun	2011	566.35	8.32	11399	16378.02	6046	182011417	
jul	2011	571.68	8.71	10266	16081.12	6049.25	168294991	
aug	2011	578.79	6.65	10268	15784.22	6050.875	161842500	
sep	2011	583.99	11.88	12594	15190.41	6052.5	156796424	
oct	2011	593.76	7.86	13726	14596.61	6055.75	148210973	Test rows
nov	2011	600.37	8.56	11682	14299.7	6057.375	142628172	
dec	2011	608.34	6.46	11674	14002.8	6059	140294981	
jan	2012	615.33	12.36	6894	11637.8	6115	For prediction	
feb	2012	625.57	7.81	5144	10637.6	6153	For prediction	
mar	2012	630.55	9.82	6175	10985	6158	For prediction	
apr	2012	636.67	9.22	7348	11192.4	6178	For prediction	
may	2012	642.11	10.16	8267	11000	6231	For prediction	
jun	2012	648.92	14.15	7261	10295	6260	For prediction	Prediction rows
jul	2012	659.84	6.83	7494	10268.8	6280	For prediction	
aug	2012	664.49	5.69	5652	9235	6287	For prediction	
sep	2012	667.74	7.82	5507	9128	6358	For prediction	
oct	2012	672.06	4.57	6864	9608	6398	For prediction	
nov	2012	674.1	5.68	6875	9714	6493	For prediction	
dec	2012	678.03	5.97	6882	9802	6528	For prediction	

4. Material and Methods

In this paper, we apply neural network architectures that are capable of learning temporal features in data in time series prediction. The feed forward multilayer perceptron (MLP) network is used frequently in time series prediction. A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. A Multi Layer Perceptron consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network Thus, it can be used to perform a nonlinear prediction of a stationary time series. A time series is said to be stationary when its statistics do not change with time.

The multilayer perceptron consists of three or more layers (an input and an output layer with one or more hidden layers) of nonlinearly-activating nodes, one hidden layer gives fairly good result. Each node in one layer connects with a certain *weight* to every node passed to the following layer. if we have N input data, the neurons of every hidden layer must be $(2N + 1)$. NeuroSolutions for Excel Software [11] Program are used to build a Multi Layer Perceptron Artificial Neural Networks that have been used to predict the value of Aggregate Personal Consumption, Gross Domestic Investment and Short-Term Interest. NeuroSolutions for Excel Software has been selected because it provides user-friendliness, flexibility, and strong graphic capabilities with data analysis. NeuroSolutions for Excel gives the ability to visually tag data as Training, Cross Validation, Testing or Production. Besides, it trains a Neural

Network. It also tests the neural network's performance directly from within a Microsoft Excel worksheet. Reports are automatically generated showing the results.

Training is the process by which the free parameters of the network (i.e. the weights) get optimal values [12]. With supervised learning, the network is able to learn from the input and the error (the difference between the output and the desired response). The ingredients for supervised learning are therefore the input, the desired response, the definition of error, and a learning law. Error is typically defined through a cost function. Good network performance should result in a small value for the cost. A learning law is a systematic way of changing the weights such that the cost is minimized.

During the network's training, the Error Criterion component provides two values that are used to ensure the performance of the network to a particular data set, and also provide correlation.

The error function or the cost function is used to measure the distance between the targets and the outputs of the network. The weights of the network are updated in the direction that makes the error function minimum.

Mean Square Error, its normalization NMSE and the correlation. In statistics, the mean squared error (MSE) of an estimator [14] is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated.

We can calculate the Mean square error as follows:

If $\hat{Y}$ is a vector of n predictions, and Y is the vector of the true values, then the MSE of the predictor is: $MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2$

MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

Root-mean-square error (RMSE) [15] is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. RMSD is a good measure of accuracy. The normalized root-mean-square deviation or error (NMSE) is the RMSD divided by the range of observed.

Correlation is a statistical measurement of the relationship between two variables [13]. Possible correlations range from +1 to –1. A zero correlation indicates that there is no relationship between the variables. A correlation of –1 indicates a perfect negative correlation, meaning that as one variable goes up, the other goes down. A correlation of +1 indicates a perfect positive correlation, meaning that both variables move in the same direction together.

5. Experimental Results

One year delay for BulkCarrier order book variable was made, that means for example the input data for year 2010 gives the order book of year 2011 and the input data for year 2011 gives the order book for year 2012 and so on .

The model was built for the selected variables from Jan 2000 till July year 2009. And tested from January 2010 till December 2010.a prediction was made for year 2011 that gives an orderbook prediction for year 2012. A comparison was made for the real and predict value of year 2012 and gives the error.thus the prediction for year 2013 was made.

139 trained months were made, 5 months for test and 12 months for prediction. In training, at first all weights and biases are initialized. Then from inputs and targets, the outputs are calculated and compared with the targets. Thus, errors are found, feed forward multilayer perceptron is started. Delta vectors are calculated from error vectors. From delta vectors the amount of change required for weights and biases are calculated. This process is looped until the error is accepted. After the Neural Network is trained on the input data set, a new data set is presented at its input, and the network provides a prediction of Shipbuilding development Market for the next twelve months.

Multilayer perceptron was generated with input layer with 5 nodes and one output layer with one node, with one hidden layer with number of nodes as follows: (2N+1)-(N+O) where N is number of input layer and O is number of output layer.

Number of nodes in hidden layer = (2*5+1)-(5+1) = 5. That means the multilayer perceptron with one hidden layer with 5 nodes.

We can present BulkCarrier Multilayer Perceptron network as follows:

Figure 1: Multilayer perceptron for BulkCarrier order book

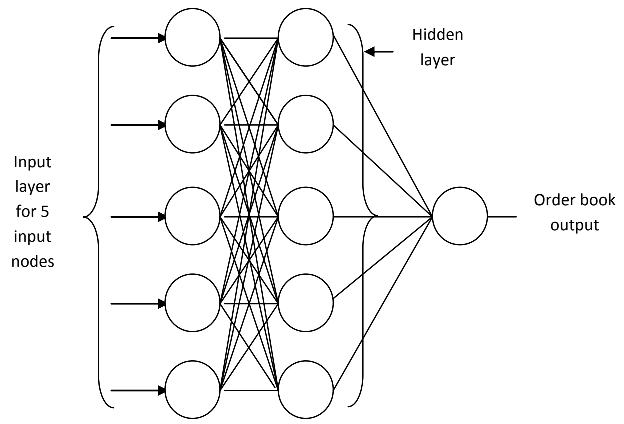
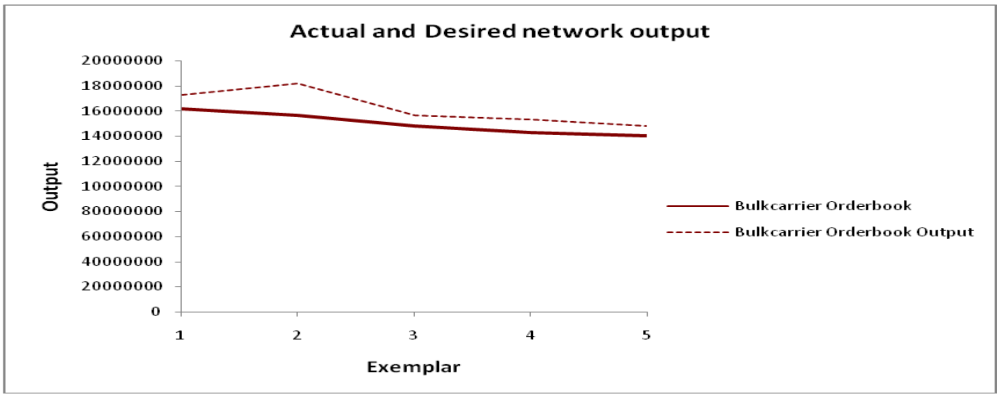


Figure 1 shows the Multilayer Perceptron for five input variable " total BulkCarrier fleet , total BulkCarrier deliveries, weighted average earnings , average dry bulk freight rates, and total dry bulk seaborne trade" and one output the BulkCarrier order book, also shows the number of nodes of hidden layers, and type of connection depending of the characteristic of the Multilayer Perceptron output.

Figure 2 shows the test output for desired and actual bulk carrier order book. The output take approximately the same direction of the desired output.

Figure 2: Desired and Actual network output



The Performance network results shown in table 4 , Mean Square Error is 0.00114 and the correlation of the data is (0.90), means that there are a good relation between the two variable.

Table 4: Performance Results

Performance	*total orderbook*
MSE	0.001144458
NMSE	0.003568745
r	0.903944765

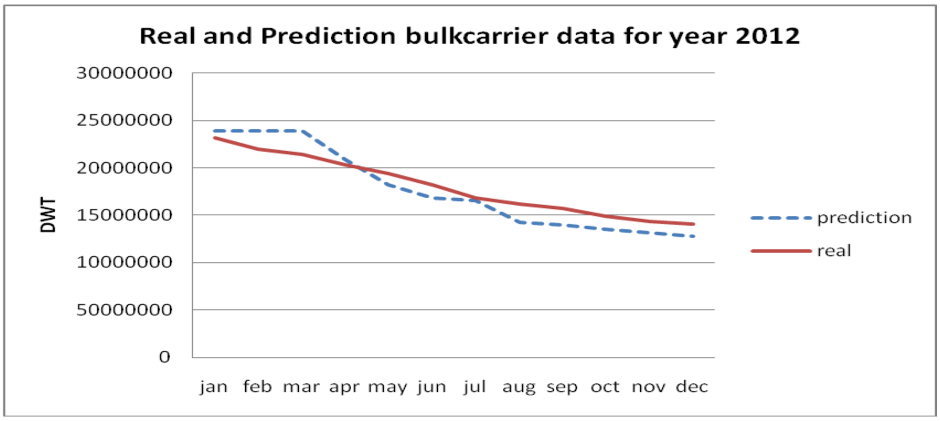
Table 5 is a comparison between real and prediction data of BulkCarrier order book for year 2012. The prediction of year 2012 is taken from the BulkCarrier prediction rows of year 2011, table 3.

Table 5: actual and desired order book for year 2012

Date	Prediction	Real
Jan	239286012	231839404
Feb	239254788	219770607
Mar	239261095	213993488
Apr	208951059	202987352
May	182460447	194041559
Jun	168422742	182011417
Jul	165346990	168294991
Aug	142815700	161842500
Sep	139477398	156796424
Oct	135195113	148210973
Nov	131474110	142628172
Dec	127662509	140294981

Figure 3 shows the prediction and real curves for BulkCarrier order book year 2012. The two curves go down because the orders of ships made in year 2008 results a big amount of ships in the BulkCarrier market with the same demand of the ships, therefore two curves go down.

Figure3: comparison of real and predict data for year 2012



The results confirm the applicability as well as the efficiency of neural networks to predict Shipbuilding Market. The neural network was able to determine the non-linear relationship that exists between the historical data supplied to it during the training phase and on that basis and make prediction of what Order book would be next twelve months.

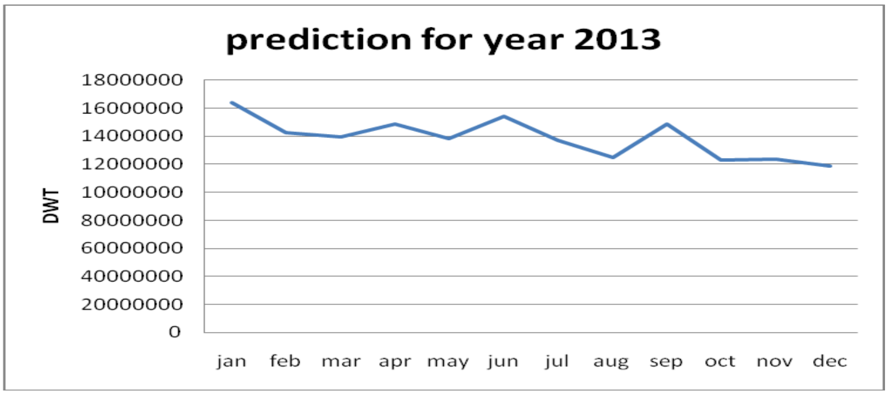
Predict and test model was applied to predict BulkCarrier order book for year 2013. Table 6 shows the Prediction for year 2013.

Table 6: Order book Prediction and real of year 2013

Date	Prediction
Jan.	163998417
Feb.	142719675
Mar.	139651239
April	148708278
May	138204348
June	154533727
July	137171156
Aug.	125326684
Sep.	148928542
Oct.	123463029
Nov.	123880663
Dec.	118939662

Figure 4 shows the BulkCarrier order book line prediction of year 2013. the figure shows that the order book volatile in narrow range, means that year 2013 will be suffer from tired market.

Figure 3: Bulk Carrier prediction for year 2013



Many expert magazine shows that the bulk carrier order book will volatile in down range in year 2012, for example E-Ship trading magazine[16] shows that " the size of the global order book is currently 46% below the 2008-peak and expected to be almost halved till year 2013".

6. Conclusion and Future work

We applied artificial neural network for building a prediction model for shipbuilding bulk carrier market. The data were collected from "Clarksons Research Studies". We select the Neuro Solution for Excel to build the neural network for five input data (total bulk carrier fleet development, total bulk carrier deliveries, weighted average earnings all bulkers, average dry bulk freight rates 1 year time charter, and total dry bulk seaborne trade). In addition, the output is the bulk carrier order book for the next twelve months, which reflect the shipbuilding market. We determined 139 months training for number of Epochs 500 and 5 test rows and 12 prediction rows.

Multilayer perceptrons (MLP) was selected with five input node and one hidden layer with 5 nodes and one output layer with one node. MLP layered feed-forward networks typically trained with static back propagation. The main advantage of MLP is that they are easy to use, and it can approximate any input/output map. The key disadvantages are that the train were slowly that other types of networks, and require many training data. We take an average of some columns like the table of "Dry Bulk Freight Rates.

We make a comparison between the prediction and real data for year 2012, the correlation is (0.903) means that both are goes to the same direction together. Finally, we applied the order book BulkCarrier model for year 2013 prediction.

The performance of the model showed that Mean Square Error is (0.001144) comparing with the other works in the same field for example the work titled “Analyzed and Forecasted Capesize Bulk Carriers Shipping Market using Artificial Neural Networks” [17], focuses one type of bulk carrier and one type of goods, using the fright rate as a desired column with Mean Square Error (0.01572). We see that Bulk carrier order book is the most oriented variable that determines the best time to build the bulk carrier ship because it referred to periodical prices when the new buildings are ordered and recorded and not when the ships are delivered. This element should be taken into serious consideration.

Our model shows that it is not suitable to build any ships at this time, although the curve in figure 3 shows a gray picture in bulk carrier building.

Finally, we present a radical tool for decision-making for financial institutions as well as a strategic tool that may give answers to ship-owners.

In future work we can perform an extra data to be an input to our model that may make the result more accurate. In addition, there is a crisis of the market from year 2008, there must be the variable that results this crises as an input to our model for more accurate results.

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