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## Freight forecasting of dry bulk market based on the BP Neural Network

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**WORLD MARITIME UNIVERSITY**

Shanghai, China



**FREIGHT FORECASTING OF DRY BULK  
MARKET BASED ON THE BP NEURAL  
NETWORK**

By

**HUANG QIANRAN**

**China**

A research paper submitted to the World Maritime University in partial fulfillments of  
the requirements for the award the degree of

**MASTER OF SCIENCE**

**ITL**

2012

## **Declaration**

I certify that all the material in this research paper that is not my own work has been identified, and that no materials are included for which a degree has previously been conferred on me.

The contents of this research paper reflect my own personal views, and are not necessarily endorsed by the University.

HUANG Qianran

2012-06-09

Supervised by

Associate Professor Gu Weihong

World Maritime University

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## Abstracts

Title of Research paper:

**Freight Forecasting of Dry Bulk  
Market Based on the BP Neural  
Network**

Degree

**M.Sc.**

The research paper is focus on the volatility factors of dry bulk market with a short-term prediction of BDI in 2012. Along the globalization is forming rapidly, the classifications of different industries is becoming more and more clear, relatively, more and more activities are bumping out. Shipping is no more than other kinds of transportation; it has been developing along the development of economy and worked for world economic activities. It has a strong relative with world economy changes, and it always changed periodically. As one of the most important part of world shipping industry, the dry bulk market is well known for its large risk and turbulence. To achieve the mentioned goal, the paper will first analyze the dry bulk shipping market based on the grey relation analysis. Started with the relationship of elements of fluctuation of dry bulk market, and then, using the Gray Relational Analysis to discuss the relevance of them. The thesis will analyze their relationship with four elements: world economic, capacity supply, freight (BDI) and shipping cost (fuel prices). Secondly, to forecast the dry bulk market base on the BP Neural Network. Finally, based on the above result, make a short-term prediction of dry bulk market.

**KEYWORDS:** Dry Bulk Market, World Economic Market, BDI, Seaborne Trade, Capacity Supply, Grey Relational Analysis, BP Neural Network

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## **List of Abbreviations**

BDI	Baltic Dry Index
BFI	Baltic Freight Index
BCI	Baltic Capesize Index
BPI	Baltic Panamax Index
BSI	Baltic Supermax Index
BHMI	Baltic Handymax Index
DWT	Deadweight
GDP	Gross Domestic Product
YOY	Year Over Year

# **Chapter 1 Introduction**

## **1.1 Background**

Along the globalization is forming rapidly, the classifications of different industries is becoming more and more clear, relatively, more and more activities are bumping out. Shipping is no more than other kinds of transportation; it has been developing along the development of economy and worked for world economic activities. It has a strong relative with world economy changes, and it always changed periodically.

As one of the most important part of world shipping industry, the dry bulk market is well known for its large risk and turbulence. It is characterized with diversities and complications. The year of 2008 is the best argument. Since December, 2008, the financial crisis and economic recession dominated the international community, which put strong pressure on maritime sector. Specifically, from May 20<sup>th</sup>, 2008 the BDI of 11793 points jump to 663 points on December 5<sup>th</sup>, 2008, which the decline rate of 94%.

Before the 1980s, the developed countries import raw materials from developing countries, while, export manufactured goods to them, while, now is just the opposite. This change makes it rely on China's oil; coal importing countries such as South Korea and Japan have to turn to the Middle East, Australia, Africa to import the needed energy and resources, which leads to the change of the structure of cargo flow and maritime demand. Shipping same as other modes of transport is a derived demand. It derivative from the national economic development and services for the international trade, so that shipping development has high relevance with the development of world economy, and presents certain periodicity.

As an important part of the shipping market, international dry bulk shipping market due to its many types of goods, variety of goods production cycle, transport means each are not identical, and suffering from the world economic and political environment, economic geography, development level of economic and industrial structure characteristics and other factors. Dry bulk market is a fully competitive market, which is recognized as one of the most volatile of transport market. To analysis the volatility and cyclical change of dry bulk market, must start with the two-way analysis of economic market and shipping market. Market analysis is necessary, because all of the market is rapidly changing.

Because all of the market is vary from minute to minute. Only to raise not only not rise or drop down of the market will inevitably does not exist. Just in the rising and falling market, adventurer receive stimulation, speculators find opportunities, the operator of the ship get exercise, which lead the whole shipping industry make optimization and development. To the owner of the ship, in the changing market, a decision may help them to be nouveaux riches overnight, may also make it instantly go bankrupt. Therefore, the most popular topic of the shipping industry is " *When and why did the dry bulk shipping market change?*"

## **1.2 Objectives of the Study**

All the markets are changeable; one decision could make a great difference. Therefore, the first objective of the paper is to *investigate* the volatility of the dry bulk market. The second objective is to *find* the impact factor of the fluctuate market through the market periodical theory. It will be very helpful for analyze the market nowadays. The third objective of the paper is to *predict* the dry bulk market in a short-term through the above study.

### 1.3 Methodology

The purpose of the paper is to *analyze* the fluctuation of dry bulk market and *predict* the market in a short term. To achieve the mentioned goal, the paper will first analyze the dry bulk shipping market based on the grey relation analysis. Started with the relationship of elements of fluctuation of dry bulk market, and then, using the Gray Relation Analysis to discuss the relevance of them. The thesis will analyze their relationship with four elements: world economic, capacity supply, freight (BDI) and shipping cost (fuel prices). Secondly, to forecast the dry bulk market base on the BP Neural Network with the tool called Matlab. We choose the BDI to reflect the situation of dry bulk market to make the prediction. Finally, based on the above result, make a prediction of dry bulk market in short-term.

### 1.4 Outline of the Paper

**Chapter 2, literature review**, intends to overview relevant research papers on the dry bulk market and the application of theory of Wavelet Analysis. **Chapter 3, analysis of the volatility of dry bulk market**. In this chapter, four elements will be presented and analyzed for the fluctuation of dry bulk market. **Chapter 4, analysis and prediction of the dry bulk market based on the BP theory of wavelet analysis**. Use the BDI data from 2011/01/04 to 2012/04/25, totally 327 group data to do the BP neural network. According to this result, analyze the periodical changing rule and frequency of historical dry bulk market and make the prediction in short term. **Chapter 5, conclusions**. The summary of findings and limitations of this study.

## **Chapter 2 Literature Review**

### **2.1 Researches on Dry Bulk Market**

Seaborne trade is an essential component of world economic activities. As the dry bulk market is the main market of seaborne trade, dry bulk market has some relevance with world economic. Lundgren (1996, p. 5), 'in many of the efforts made to explain economic growth, revolutionary improvements in transport technology have often been pointed out as a key factor'. In addition, he reviewed the relationship between bulk trade and maritime transport costs and pointed that improved shipping technology and reduced transport costs have encouraged world bulk trade.

Along the globalization is forming rapidly, the classifications of different industries is becoming more and more clear, relatively, more and more activities are bumping out. Shipping is no more than other kinds of transportation, it has been developing along the development of economy and worked for world economic activities. In certain extent, the shipping's periodicity reflects the cycle of world economic. Stopford (2009) investigated the market in last three decades. The result showed that the ups and downs of the market interact to the demand and supply. Demand for shipping directly affected by the economic and trade development, while, the supply of shipping has its own characteristics, such as ship price elasticity of supply is weak, and it increases and decreases have the significant hysteresis quality.

Among all the shipping market, the dry bulk is the most volatile one for its risky time-varying freight. Discussions on the freight and other time-vary behaviors of dry bulk market have been studied by plentiful researches. Köhn and Thanopoulou (2011) made an assessment of a quality segmented charter market with dry bulk time-charter rates (Panamax) from 2003-2007, which is the shipping boom period, through generalized additive models. The results pointed that freight differentiation has become visible in booming markets with high freight rates. They also quantified

quality in many places such as place of delivery, charter length and days from forward to delivery, as well as for vessel size and consumption. Xu, Yip and Marlow (2011) through two steps, which are measuring freight rate volatility and analyzing the relationship between freight volatility and fleet size growth, to emphasize the relationship between the time-varying volatility of dry bulk freight rates and the change of the supply of fleet trading in dry bulk markets. Kavussanos and Alizadeh (2002a) investigated the expectations hypothesis of the term structure in the formation of period rates, which requires long-term charter rates to be a function of a series of short-term contracts within the life of a long-term contract and used a battery of tests to examine the validity of the expectations hypothesis for a variety of size categories and different length charter rates. Kavussanos, Visvikis and Batchelor (2004) investigated the impact of the introduction of Forward Freight Agreement (FFA) trading on spot market price volatility in two panamax Atlantic and two panamax Pacific trading routes of the dry-bulk shipping industry and found that only in voyage routes may the reduction in volatility be a direct consequence of FFA trading.

Besides, the market has other variables called 'noise' such as seasonality. Kavussanos and Alizadeh-M (2001) investigated the nature of seasonality in dry bulk freight rates, and measures and compares it across freight rates of different vessel sizes, contract duration and market conditions. The result indicated that the larger vessels suffering the higher seasonal fluctuations than smaller vessels in spot rates section. Besides, for each vessel size, the seasonality declines or ups depend on the contract duration and different market conditions.

## **2.2 Difference Forecasting of Dry Bulk Market**

The dry bulk market is the most challengeable market for its risky freight rate, which is a big issue to understand or control, so the forecasting of dry bulk market is much important for investors who own or operate vessels. To a lesser extent, some researches tend to lack mathematic method to analyze the historical data, relying

instead on describing situation only. For example, Wei (2010) described that from the demand of dry bulk shipping, the growth in the second half of the year will be less than the first half. While, the changes in the structure of trade lead to the growth of maritime mileage will extend the vessel's turnaround time, and the excess capacity is the most negative impact on the market. In addition, Wang and Liu (2010) got the conclusion that the situation in 2010 will be better than 2009 after summing the data from situation of world and China economic, the demand of steel and iron ore, and the supply of capacity in the market.

More researches focus on the prediction with using the mathematic model in earlier time. Article by Veenstra and Franses (1997) developing a vector autoregressive model to a sample of ocean dry bulk freight rates. Evidence provided by cointegration tests points to the existence of stable long-term relationships between the series even though they are found to be non-stationary and an assessment of the forecasts derived from the model suggests that the specification of these long-term relationships does not improve the accuracy of short- or long-term forecasts. Glen and Martin (2004) did the similar but more entirely research on modelling the behaviour of demand, trying to test assumptions about expectations, testing for conditional heteroscedasticity, examining seasonality, and trying to model the behaviour of ship prices. Jiang (2009) applied the BP filter method chosen to decompose BDI into cycle and tendency. The result showed that in the dry bulk cargo shipping market long term periodical fluctuation stay with the short term periodical fluctuation. Latterly, the fuzzy time series method is widely applied. Duru (2012) developed an improved fuzzy time series method via adjustment of the latest value factor and previous error patterns. He applied fuzzy integrated logical forecasting (FILF) and extended FILF (E-FILF) algorithms for short term forecasting purposes. The empirical result of the Baltic Dry Index (BDI) indicated the superiority of the proposed approach compared to conventional benchmark methods. Similarly, Duru, Bulut and Yoshida (2012) did the research to improve the fuzzy logical forecasting model (FILF) by utilizing multivariate inference and the partitioning problem for an exponentially distributed



time series by using a multiplicative clustering approach. Besides, fuzzy time series (FTS) shows its superiority more frequently with a growing study field in computer science.

### **2.3 The Application of BP Neural Network**

After decades of development, has formed hundreds of artificial neural network. In 1974, P. Werbos in his doctoral thesis presented a first for multilayer network learning algorithm, but the algorithm does not receive enough attention and wide application. Until the 1980s, David Rumelhart, Geoffrey Hinton and Ronald Williams, David Parkr, and Yannn Le Cun were discovered BP algorithm independently. In 1986, the United States of California PDP (parallel distributed procession) group has published a book called Parallel Distributed Processing, which used the algorithm in neural network research, to make the multilayer neural network learning algorithm BP algorithm famous. The algorithm to train the neural network, called the BP neural network.

According to experts in the relevant research written by Jin (2001), BP the research current situation of the network can be divided into three categories: parameter improvement research; merged with other optimization algorithm; topology optimization.

Improvement of the parameters of mainly includes adding momentum item, improved error function, parameter self-adjusting, the selection of original weight and improved activation function.

Have been some researches, obvious effect with wide application is the " adding momentum item", increase the momentum can play a damping role in the adjustment of the time  $t$ . Pearlmutter (1992) said that when the error surface appear suddenly ups and downs, we can reduce the oscillation trend to improve the training speed. On the

basis of adding momentum, he introduced quadratic momentum into the BP network. While, we can see there is another way to improve BP network called improved error function. The error function of the standard BP algorithm is the absolute value in the form of this absolute form of the error function is difficult to effectively describe the sample precision, leading to poor network convergence speed. The major improvements: Veenstra and Franses (1997) presents a new type of relative errorfunction, and Gibb (1996) putted the absolute accuracy and relative accuracy to describe the training error. The learning rate is a key factor to affect the convergence rate, has a major impact on the success or failure of the BP algorithm. The learning rate is actually a step along the negative gradient direction. The learning rate is too small to make training an increase in the number of flat areas, so that have to increase the value of learning rate. Better idea of the learning rate is increase or decrease at the right time. Now proposed view about method gradually smaller learning rate adjustment method from Liu (2005), and the use of linear adaptive variable step size from Deng and Sun (1993). Dong (2000) and Yan (2000) both of them study the initialization of the weights. Initialization of the weights has a great influence on the pros and cons of the BP neural network training results. If the initial weight value is too large, the Sigmoid function will be saturated at the beginning of the training, the network into local minima near the initial point of priority. Generally, the connection weights initialized to random numbers within the range of  $[0,1]$ . In the BP network hidden layer neurons often uses the Sigmoid function as the activation function. Use the Sigmoid function is easy to appear the "saturation" phenomenon, thus affecting the network convergence speed. Many experts introduce the improved methods: using derivative promotion approach, using a new activation function: the case of the hyperbolic tangent function, Gauss function, wavelet function from Wu (1996). Many researches studied put the other optimization ideas into BP neural network include: Genetic Algorithm from Holland (1997), Simulated Annealing from Kirkpatrick (1983), and Chaos Optimization Algorithm from Lin and Jiang (1997).

Li (1999) and Zhai (2003) introduced genetic algorithm in the BP neural network mainly used to optimize the initial weights, the BP neural network weights were randomly initialized and the error metric function to minimize the fitness value criteria genetic algorithm to optimize the search operation, after excellent individual (optimized weights) after evolutionary iteration. In Wang and Zhang (1998), they thought that important reason to improve BP neural network effectively is that simulated annealing algorithm, changed increase the capacity of "climbing" instead of original way to pursuit of error decreases blindly, which make the BP network can escape from the local excellent and the globally optimal. In the field of neural networks, chaotic optimization has been successfully used to solve the BP network weights optimization written by Tang and Zhang (1998).

## **2.4 Summary**

From all the above researches, we can get several findings. First, dry bulk market is an essential component of shipping market and it is the most challengeable one for its risky freight. Second, there are plenty method to forecast the dry bulk market prospect. Third, the BP Neural Network has the obvious superiority on time series data.

However, we can find the deficiencies easily. There were some researches studied on the cycling volatility relationship of dry bulk market and world economic market, while, the studies more focus on the qualitative research with lack of quantitative research. This Paper will use the Grey Relation Analysis to study this relationship, to find out the most important factor of fluctuation. After all, this Paper will apply BP neural network model into the prediction of BDI in the short-term from 2012.

## **Chapter3 Analysis of Correlation between the Dry bulk Market and World Economic Market**

### **3.1 Methodology**

#### 3.1.1 The Method of the Grey Relational Analysis

The Gray Relation Analysis scales the relevant degree of factors according to the similar or alien degree of the expansibility among factors, which points out the character and degree of dynamic relevancy. If the two elements have the similar expansibility, they have high degree of relevancy; otherwise, they have low relevancy. Therefore, the grey relational analysis provides quantitative measurement for the development trend of the changes of system, which, very suitable for dynamic analysis of the course.

#### 3.1.2 The Initial Factors Considered

There are many factors affect the dry bulk market volatility, generally, it must be a positive factor make the dry bulk market rising, while, the weakness of the market caused by negative factors. Finally, under the force of various factors, dry bulk market suffering the volatility of the market.

Based on this view, the paper initiate the study of the factors that affect the dry bulk market volatility with the discussion of the correlation between the factors. Mainly through the study of four areas: economic factors (unexpected events), capacity supply, capacity demand (seaborne trade) and policies (shipping costs). We can see the factors visually from Figure 1.

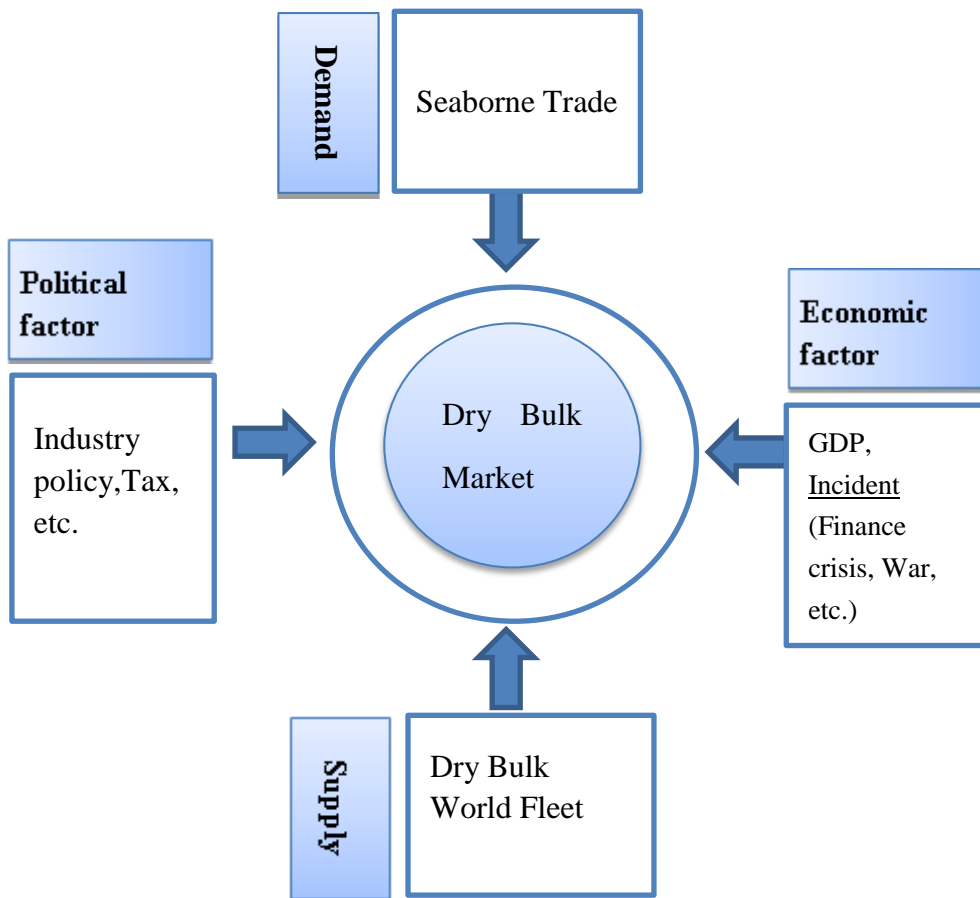


Figure 1 Factor of dry bulk market volatility

Source: Own presentation

These factors are determined by the following key indicators respectively. It is important to note that the paper used the Baltic Dry Index (BDI) to represent the situation of dry bulk market. While, the political factor is cannot be quantified easily, so this factor will be discuss in the later section.

#### (1) BDI

This paper, use the Baltic Dry Index to reflect the freight rate. In the international dry bulk shipping market, BDI published by the Baltic Exchange, can reflect the world dry bulk shipping market's general tariff level objectively with highly authoritative and representative. Therefore, BDI is known as the "barometer" of international dry bulk shipping market.

February 1st, 2012, BDI Index closed at 662 points to new lowest since December 5th, 2008. BDI index hit a new lowest, mainly because the calculation has been adjusted. Began with July 1st, 2009, in order to promote derivatives trading, the Baltic Exchange used rent data calculation to the Baltic Dry Bulk Freight Index (BDI). BDI calculated the index of Baltic Capesize ship, Panamax, super Handymax and Handysize vessel charter market, each ship each accounted for 25% of the BDI. Specific calculation formula is:  $BDI = ((CapesizeTCavg + PanamaxTCavg + SupramaxTCavg + HandysizeTCavg) / 4) * 0.113473601$ . Previously, the calculation formula used by the BDI index is  $BDI = (BCI + BPI + BSI + BHSI) / 4 * 1.1926213627$ . According to this formula, the BDI index of February 1st, 2012 should be 946 points. While, due to the limitations on the calculation and model, the paper ignored the calculation method of changes on the BDI.

(2) Supply factor (fleet capacity) of the market:

In this paper, deadweight (DWT) of world fleet to is used to reflect the capacity supply. The capacity of the dry bulk shipping market is in a certain period of time, all the carrier, in variety of freight rate, are able and willing to provide the amount of tonnage, that is, net dead weight of world fleet in a certain period of time. A period of international dry bulk ship supply is equal to the period of international dry bulk shipping market ship's in possession minus the period of storage quantity. The indicators reflect the whole market capacity; the changes are affected by the amount of newbuildings and dismantling old boat. The increase of ship supply means that there is more intensive competition in the international dry bulk shipping market competition, which will have pressure on trend of market.

(3) Demand of shipping:

This paper adopts the dry bulk seaborne trade to reflect the demand of shipping. International dry bulk seaborne trade mainly include iron ore, coal, grain some big deal volume bulk cargoes and steel, cement, some parcel dry bulk cargoes. The indicator is the main driving force of development of the market, because there is a

demand to supply, ultimately, supply changes in the final analysis is by demand. Therefore, the change of index adumbrative the trend of market demands in certain degree.

(4) Shipping cost:

Factors affecting the dry bulk shipping costs, including fuel costs, port charges, crew labor costs. Among them, marine fuel consumption account for more than 25% of the fleet's operating costs has become the biggest factor constraining the profit of fleet operators and ship owners. Currently, in today's ship fleet the trend of large-scale is more and more obvious, with the increasing of the ship deadweight tonnage, the increase of large bulk carriers' fuel consumption is quite huge. Therefore, the paper selected fuel prices to reflect the relative cost of shipping.

**3.2 Analysis of Relevance among the Fluctuations of Dry Bulk Market**

The paper evaluated international dry bulk shipping market volatility factor which mentioned above as the analysis of indicators, the sample for these indicators use 1999-2011 annual growth ratio<sup>1</sup>. Growth of global GDP is used as world economic indicators; specifically indicator variable in Table 1.

Table 1 Factors in the Grey relational analyze model

Index	Value
BDI	X <sub>0</sub>
All Bulk World Fleet (10 <sup>6</sup> DWT)	X <sub>1</sub>
World GDP (year growth %)	X <sub>2</sub>
Dry Bulk Seaborne Trade (10 <sup>6</sup> t)	X <sub>3</sub>
Worldwide Bunker Price (\$/t)	X <sub>4</sub>

Note: Considering the port of Singapore is international famous supply port, so use the Singapore harbor 380CST price as a marine fuel prices.

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<sup>1</sup> Annual growth ratio of BDI in 1999 equals the value of BDI in 1999 minus the value of BDI in 1998. The same situation of all the data (X<sub>0</sub>, X<sub>1</sub>, X<sub>2</sub>, X<sub>3</sub>, X<sub>4</sub>).

Table 2 Index's value

<b>Year</b>	<b>X<sub>0</sub></b>	<b>X<sub>1</sub></b>	<b>X<sub>2</sub></b>	<b>X<sub>3</sub></b>	<b>X<sub>4</sub></b>
1999	335.00	-2.70	2.20	73.00	49.51
2000	282.00	2.10	-0.20	258.00	56.90
2001	-430.00	7.40	0.30	66.00	-25.60
2002	-5.00	11.00	0.60	194.00	15.80
2003	1552.00	6.30	0.70	185.00	23.10
2004	1749.00	6.90	1.30	286.00	8.30
2005	-1230.00	8.80	-0.30	217.00	81.60
2006	-14.00	31.80	0.60	256.00	51.30
2007	4013.00	12.60	0.20	263.00	59.60
2008	-1182.00	33.40	-2.50	198.00	132.80
2009	-3429.00	25.30	-3.60	-271.00	-133.70
2010	116.00	40.40	5.90	607.00	92.20
2011	-1235.00	79.20	-1.40	322.00	182.80

Source: Clarkson SIN 2005

Analysis steps:

(1) Standardized (dimensionless): because of the different unit of the factors in the system of column data may affect the result of the calculation, it is not easy to compare or in comparison to get the correct conclusion, so in the grey correlation degree analysis generally have a standardized data processing based on the reference sequence as the reference point, the series standardization shown in table 3.

Table 3 Standardization of data

<b>Year</b>	<b>X<sub>0</sub></b>	<b>X<sub>1</sub></b>	<b>X<sub>2</sub></b>	<b>X<sub>3</sub></b>	<b>X<sub>4</sub></b>
1999	1.00	1.00	1.00	1.00	1.00
2000	0.84	-0.78	-0.09	3.53	1.15
2001	-1.28	-2.74	0.14	0.90	-0.52



2002	-0.01	-4.07	0.27	2.66	0.32
2003	4.63	-2.33	0.32	2.53	0.47
2004	5.22	-2.56	0.59	3.92	0.17
2005	-3.67	-3.26	-0.14	2.97	1.65
2006	-0.04	-11.78	0.27	3.51	1.04
2007	11.98	-4.67	0.09	3.60	1.20
2008	-3.53	-12.37	-1.14	2.71	2.68
2009	-10.24	-9.37	-1.64	-3.71	-2.70
2010	0.35	-14.96	2.68	8.32	1.86
2011	-3.69	-29.33	-0.64	4.41	3.69

(2) Series calculation including  $|X_0(K)-X_i(K)|$ , max value, min value, and resolution ratio  $\beta(0<\beta<1$ , assumed  $\beta=0.5$ ), shown in table 4.

Table 4 Series of difference

Year	$ X_0(K)-X_1(K) $	$ X_0(K)-X_2(K) $	$ X_0(K)-X_3(K) $	$ X_0(K)-X_4(K) $
1999	0.00	0.00	0.00	0.00
2000	1.62	0.93	2.69	0.31
2001	1.46	1.42	2.19	0.77
2002	4.06	0.29	2.67	0.33
2003	6.97	4.31	2.10	4.17
2004	7.78	4.63	1.30	5.05
2005	0.41	3.54	6.64	5.32
2006	11.74	0.31	3.55	1.08
2007	16.65	11.89	8.38	10.78
2008	8.84	2.39	6.24	6.21
2009	0.87	8.60	6.52	7.54
2010	15.31	2.34	7.97	1.52
2011	25.65	3.05	8.10	7.38
min	0.00	0.00	0.00	0.00

max	25.65	11.89	8.38	10.78
-----	-------	-------	------	-------

The  $\min_1 \min_k |X_0(K) - X_i(K)|$  is 0,  $\max_1 \max_k |X_0(K) - X_i(K)|$  is 25.65.

(3) Correlation coefficient  $\xi_i(k)$  calculation: a reference sequence of  $X_0$  with a plurality of comparison of the sequence  $X_0, X_1, \dots, X_n$ . The correlation coefficient of each reference sequence and comparative sequence in each time has the formula as follows,

$$\xi_i(k) = \frac{\min_1 \min_k |X_0(K) - X_i(K)| + \xi(k) \max_1 \max_k |X_0(K) - X_i(K)|}{|X_0(K) - X_i(K)| + \xi(k) \max_1 \max_k |X_0(K) - X_i(K)|}$$

In the formula  $\min_1 \min_k |X_0(K) - X_i(K)|$  is the min value of the absolute difference;  $\max_1 \max_k |X_0(K) - X_i(K)|$  is the max value of the absolute difference.

The results shows in the following table 5.

Table 5 Calculation of correlation coefficient

Year	$\xi_1(k)$	$\xi_2(k)$	$\xi_3(k)$	$\xi_4(k)$
1999	1.00	1.00	1.00	1.00
2000	0.82	0.85	0.86	0.54
2001	0.84	0.85	0.85	0.77
2002	0.88	0.99	0.99	0.64
2003	0.89	0.90	0.89	0.63
2004	0.98	0.98	0.98	0.56
2005	0.90	0.94	0.96	0.45
2006	0.93	0.93	0.90	0.58
2007	0.89	0.89	0.91	0.46
2008	0.93	0.94	0.90	0.71
2009	0.94	0.86	0.87	0.69
2010	0.93	0.89	0.89	0.84

2011	0.89	0.88	0.92	0.75
------	------	------	------	------

(4) Calculation of correlation degree: because the correlation coefficient is the Relevance value of the reference sequence and comparative sequence in each time, so its number more than 1, and the information is too scattered to conduct an overall comparison. Therefore, it is necessary to calculate the average value, as the correlation degree quantity of the reference sequence and comparative sequence. The correlation coefficient degrees  $r_i$  of average value of  $X_i$  associated with  $X_0$  has the formula as:  $r_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k)$ .

(5) The results of the calculation:  $r_1=0.90$ ,  $r_2=0.91$ ,  $r_3=0.93$ ,  $r_4=0.67$ , comparing with each value, the larger the value is, the higher the correlation degree is.

The results show that the correlation degree  $r_2$  of variable  $X_3$  and  $X_0$ , reached 0.93, describing of the high correlation degree between the international dry bulk shipping trade volume and BDI. BDI is known as the "barometer" of the international dry bulk market, while the dry bulk seaborne trade is also a main index reflect the dry bulk market situation, so these two factors have a most closely correlation. The correlation degree of the BDI with the world economy and the shipping supply, reached 0.91 and 0.90, respectively, a description of the world economy and shipping supply and BDI are highly related. In these four indexes, the correlation of the bunker price and BDI is slightly lower is 0.67.

### 3.3 Analysis of the Factor of Dry Bulk Market Volatility

#### 3.3.1 Factor of Demand

As mentioned previously, the international dry bulk shipping market demand is mainly derived from the composed of international trade, especially in China or other

developing countries has a large-scale production of raw materials and infrastructure needs. These demands account for very large proportion in the dry bulk market total demand. Therefore, the nature of dry bulk market demand determines it will be directly influenced by the international trade situation.

Dry bulk market demand is derived. If a commodity or labor demand is caused by other goods or services demand, then the goods or services is a derived demand. International dry bulk trade led to the needs for long distance flows of goods, and in order to meet this demand, dry bulk shipping market emerge as the times require. The development of international trade depends on the world economy entirely, so the primary factor to influence of dry bulk market is the changes of world economy. The comparison of growth rate of dry bulk seaborne trade the global GDP also fully permitted the conclusion, shown in the figure 2.

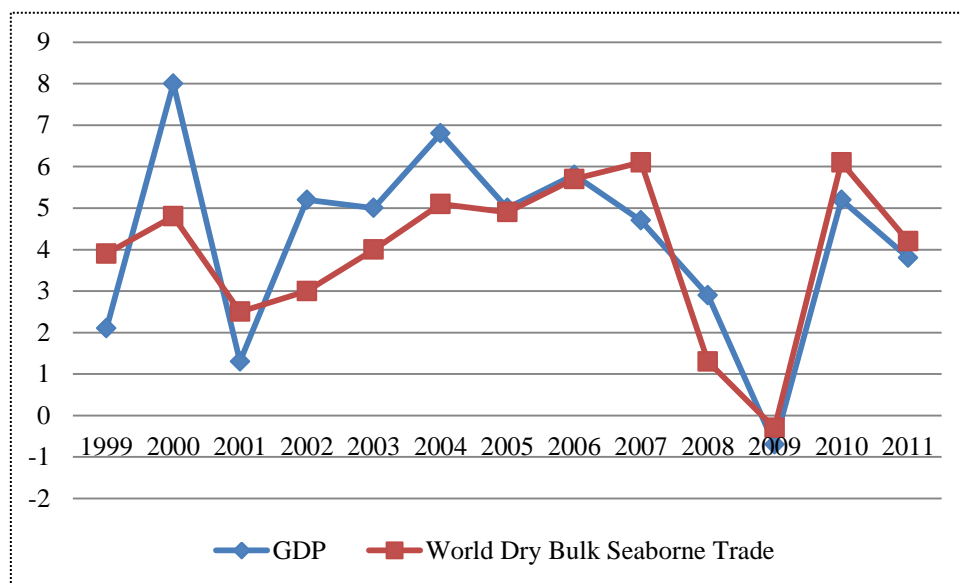


Figure 2 The relationship of growth rate of GDP and dry bulk seaborne trade

Source: Arrangement according to Appendix I

From figure 2, we can see that, when the world economic has strong incentive, international trade corresponding to rise rapidly, along with huge demand for shipping; when the world economy into recession, international trade shrinked, the shortage of cargo will depress the shipping market eventually.

### 3.3.2 Factor of Capacity Supply

The products provided by the shipping supply is service, the production activities of the shipping companies are changes of shipping object's space position, with no new substance is produced. Same as the service industry, production and consumption of dry bulk market supply are performed at the same time, transport the products cannot be separated from the production process and independent existence, this is the non-storage transport product, which determines the transport equipment can adapt to the dry bulk market demand changes through capacity increase or reduce. However, transport capacity growth due to the longtime of manufacturing ship lead to the growth of transport capacity has certain lag, cannot immediate reaction to the market. Therefore, many market participants will reserve a certain capacity to adapt to changes in market demand, it may probably adapted to the dry bulk shipping market demand growth opportunities, while, also may lead to the dry bulk market supply and demand imbalance, especially the risk of oversupply increases.

From 2005 to 2007, global economy antibiotics's in the round, international trade quantity rise steady. The world dry bulk demand gross achieves 29.93 billion tons, among them, grain transport capacity is relatively stable, which had little effect on the changes of market demand, the main factor leading to changes in market demand are iron ore and coal. In 2007, the global demand for coal transport about 7.7 billion tons, growing 4% by compared with 2006; global steel output exceeds 13 billion tons, growing 7.7%, resulting in increment of iron ore and steel dry bulk cargo transport demand about 0.75 billion tons, is the important factor of international dry bulk shipping market demand increasing. In this three years, the global dry bulk shipping market continued to brush new historical high, also continuously presents the ups and downs of change, high vibration amplitude is increased ceaselessly, in May, 2008 reached the new highest, 11793 point. Under this positive environment influence, most shipping companies have strong confidence in the shipping market for next few years, leading a substantial increase in newbuildings orders.

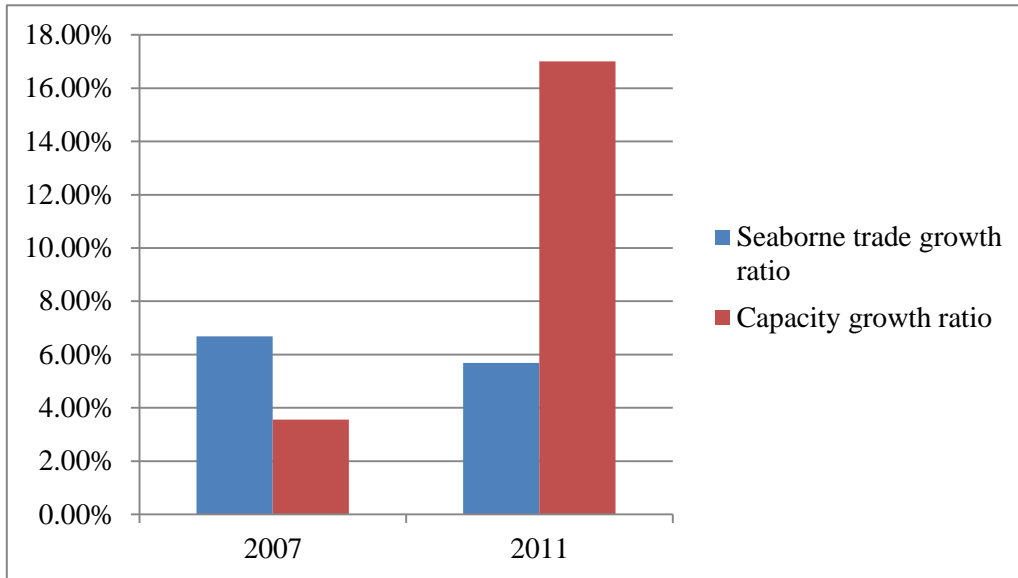


Figure 3 Demand and supply of 2007 and 2011

Source: Arrangement of Appendix I and Appendix II

However, due to the American Subprime Mortgage Crisis eruption and then evolved into a global financial crisis, the global economic setback, coupled with the Chinese economy soft landing, shipping market also dropped into the "winter" period. In the past two years, there are a number of shipping companies unable to afford the high cost of newbuilding and giving up the order. However, with the shipyard has completed the new shipbuilding orders in 2010, 2011, there is still a large capacity swarm into the shipping market in 2010, 2011, and 2012. Coupled with the reduction of seaborne trade, the dry bulk market supply capacity is much greater than demand, specific conditions are visible in figure 3. Therefore, after a slight rebound in 2009, and then the BDI into a sustained downturn in 2010, reaching the record lowest at 647 in February 2012.

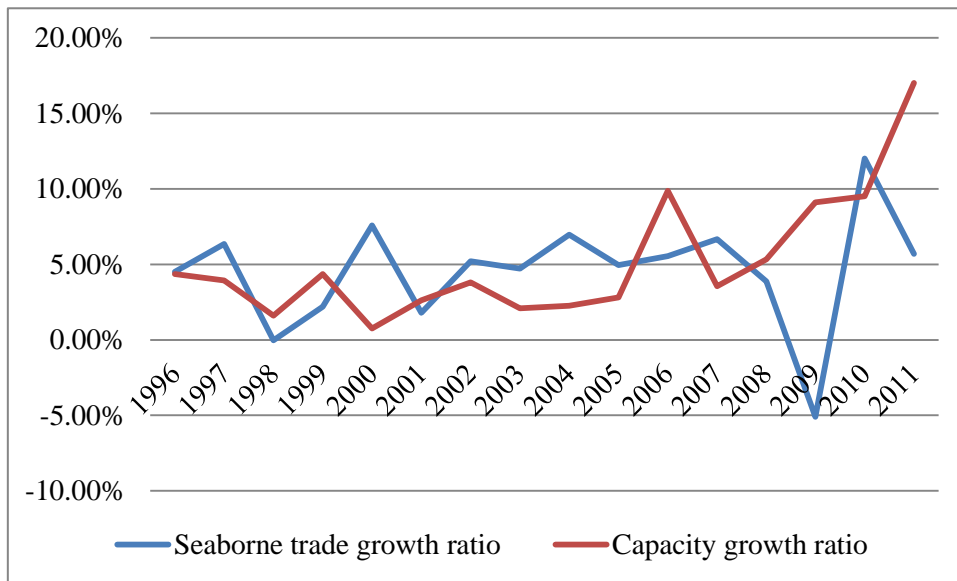


Figure 4 Growth ratio of capacity and seaborne trade

Source: Arrangement of Appendix II.

The figure 4 showed that with the time flow, the trend of dry bulk capacity became linear growth, the capacity of the change trend and the shipping volume changes toward roughly the same tendency. Due to the shipbuilding cycle effects, capacity changes will lag behind the changes of seaborne trade. In 1998The financial crisis erupted, trade volume decreased, but the reductions of supply capacity reacted in the beginning of 2000. Nowadays, on the period of depression, the world trade and economic development to reach a peak in 2007, but the new ship order will shows effects in the shipping market supply until 2009. So the growth rate of fleet capacity has a periodic fluctuation, and the fluctuation is about two years lag behind growth of dry bulk market demand. This is related to need a longer production time in building a new ship.

### 3.3.3 Factor of Economic

As mentioned above, the derivative of dry bulk market determines the prosperity of the market is closely bound up with world economy even with region economy, so, economic development is one of the important factors of the international dry bulk shipping market. Since 2000, along with the recovery of global economy, dry bulk trade volume continued to show steady growth (from the above figure 2 can also be

seen). Especially since 2003, the United States of America Iraq war had driven the rapid growth of the United States' economy. Under this situation, dry bulk market also produced positive change. In addition, China has always strong demand of dry bulk cargo, dry bulk cargo market gradually rise with shocks. However, with the outbreak of the Subprime Mortgage Crisis in the second half of 2007 of the United States, and then evolved became a worldwide financial crisis, which led to a significant drop of the growth of global economy, also makes the dry bulk market slump, entered "the cold winter". The contrast of growth rate of the world economy and the growth rate of dry bulk seaborne trade is shown in figure 5 specifically.

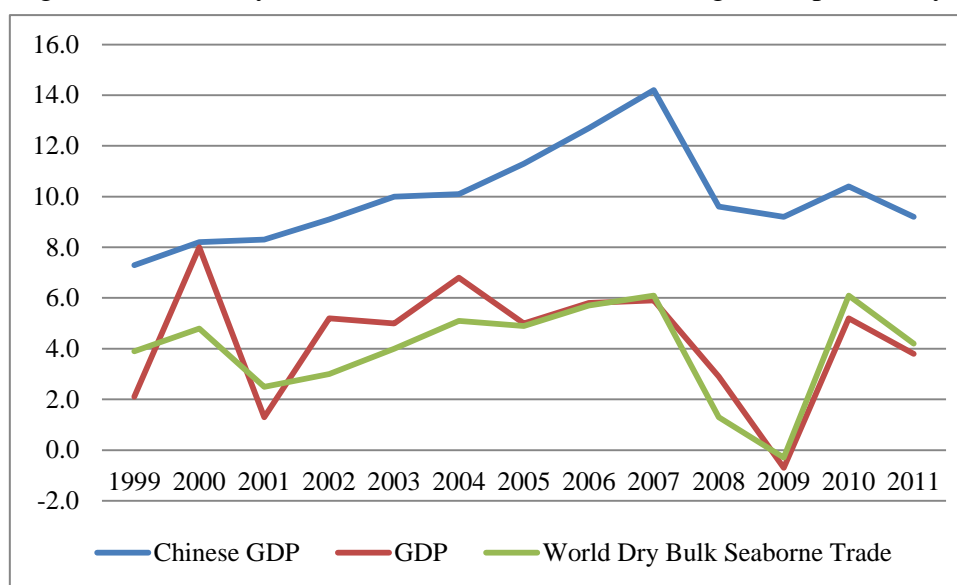


Figure 5 World economic growth and dry bulk shipping growth changes

Source: Arrangement of Appendix I and Appendix II.

According to the figure 5, the world economy influence dry bulk market fluctuations mainly reflect in two aspects. One aspect is the internal mechanism, from world economic cycle fluctuation. The research shows that, in normal circumstances, the world economy in four to five years for a cycle. The periodic wave motion of economy leads to the development of shipping demand showing a periodic variation. In recent years, China's economic development for dry bulk market impact is also growing, as a new global economy manufacturing center; China has become the main drive force of dry bulk market. China is still in the middle stage of industrialization, vigorously develop urban construction and the equipment manufacturing industry



makes China become the first importer for the iron ore and coal. The upgrading of consumption structure and upgrade of industrial structure are the key driving force of rising phase for China's current stage of economic periodic, which maintain the economic growth rate of around 10%, peaked at 14.2% in 2007. The contribution of world economy reached 27%, so China has become the key factor to drive the dry bulk market grow. However, with the beginning of the 2008, China's economic growth is slowing down; it made more disaster on the "winter" of the dry bulk market.

Another influence aspect is reflected on the external economic impact or sudden events, such as the financial crisis, war and so on, which can be seen in figure 6.

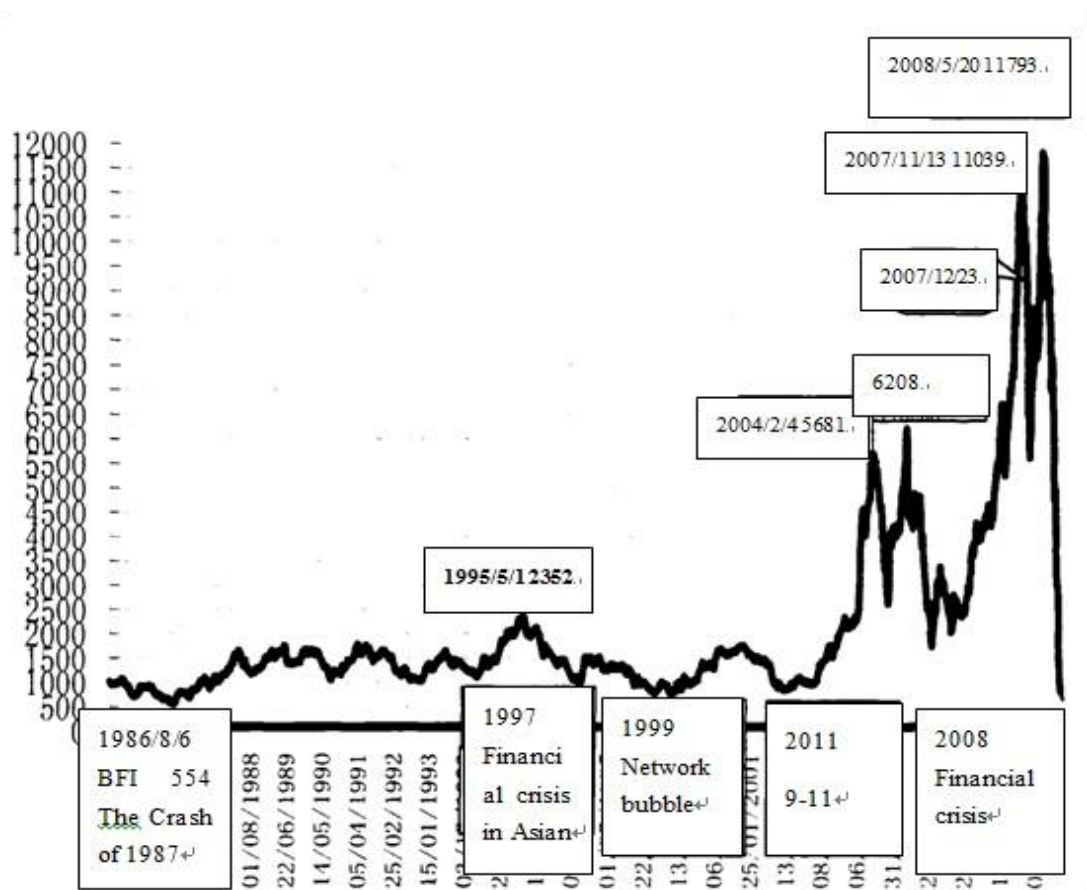


Figure 6 Historical data of BDI/BFI

Source: Liu, Z.J. (2009) *Research On the Fluctuation and Forecasting of International Dry Bulk Shipping Market Cycle Based On Wavelet Theory*. And Own Presentation.

On the other hand, the economic shock, with varying of periodic of economy, economic impact is sudden, which has more severely effect on shipping market.

Figure 6 shows the BDI fluctuations obviously, and the key point is given to describe. We can see that, every incident has a very strong influence on the dry bulk shipping market. From 1990 to 1994, there appeared 2 depressions. The background of these two depressed market is the situation in the Middle East instability leads to regional economic outlook instability caused the decline in demand. The two depressed have some features in common, such as the fluctuation of freight is mild, short cycle, coverage of regional.

From 1997 to 1999, is the severe recession of shipping market. In this recession, the market has a dramatic fluctuation. The downside is under the background of the global economic growth slowdown, including the developing countries' economy to a soft landing, while, Southeast Asian financial crisis spread to the world caused this recession radically. The steel output of developed countries fell, and the grain import country bumper harvest, the volume of grain trade reduced, as well as the coal transport distance shortened and the delivery of new vessels caused large amount of unbalance of supply and demand, resulting the international dry bulk shipping demand in the lowest point in 2008 in the recent 5 years, from 1995 to 1999.

At present, although it has been 4 years from the financial crisis outbreak in 2008, shipping market are still in a slump, and this sluggish market has an unprecedented volatility. The BDI index such as roller coaster in 2008 were completed from the highest, 11793 point tumbled to 663 points within one year; the dry bulk market amplitude nearly more than ten thousand points a short cycle. After 2008, the dry bulk market entered a continuous period of decline. The reason is that the American Subprime Mortgage Crisis evolved into a global financial crisis, almost all entities in the industry have been greatly affected, the global trade volume decreased especially changes of Chinese industrialization pattern leads the declined of dry bulk market demand. In 2010, abundant capacity inburst into the market would make this recession sustained extension. Besides, the new lowest in the 2012 the paper will discuss in the next section, so the Figure 6 did not reflect this situation.

Figure 6 shows that a sudden event always broke the whole market periodic fluctuations and then make a new cycle.

Nevertheless, economic market for shipping markets has hysteresis effect. Take the financial crisis as an example shown in figure 7.

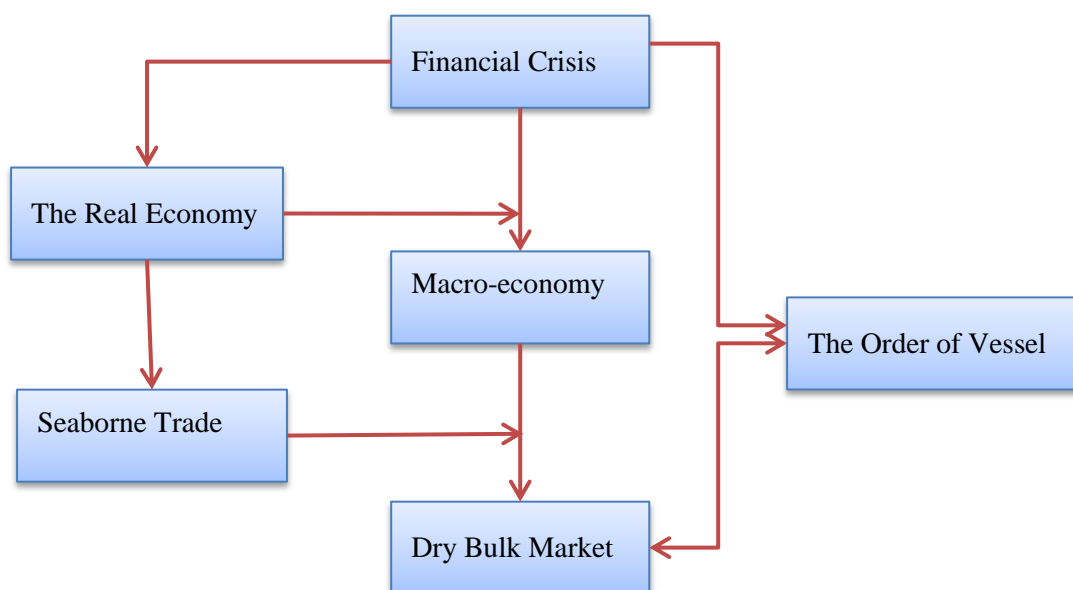


Figure 7 Hysteresis influence of financial crisis to dry bulk market

Source: Own presentation

Due to the impact of the financial crisis on the real economy is gradually conduction. Firstly, the impact will reflect on macroeconomic and financial industry, and then have a negative impact on the real economy, leading to international trade decline, the indirect effects of the shipping market, and finally reflected in the shipping industry. Orders of vessels will interaction with the shipping market eventually, which leading to oversupply, the details will be mentioned in later chapters. Development or recession of world economy, usually have six-month time to reflect on the trade, while, international trade changes in demand for dry bulk market usually requires a year's time. In other words, demand of dry bulk market is lagging behind the world economic recovery or recession for about 1-2 years. Like the Subprime Mortgage Crisis erupted in the second half of 2007, but the BDI index hit a new highest record in May 2008, while, July began a rapid decline. The changes of dry bulk market

demand lagged less than a year. We should note that with the flattening of the world<sup>2</sup>, the rapid development of global industrial chain formation and communication technology, the lag of the international dry bulk market demand has shorter trend.

### 3.3.4 Factor of Policy

The development of world economy and trade, make shipping becomes an independent material production sector, at the same time the shipping industry is connected with different type of economy, different development level and the geographic location. It is extremely complex and the fierce competition of the international environment, each country and area government tried various protection policy in order to protect and develop the local shipping industry from the competition of international shipping market. England in the Falklands War also reflect the merchant is a part of the national military strength, so the development of shipping industry and supply influenced by national polity, government policy and military needs at the beginning. Therefore, shipping market development is not entirely a market behavior, for example, the revitalization plan of Chinese shipping industry, the government put the Warranty Policy. In fact, when the shipping market cannot fully digest the capacity of the case, promote the supply for the shipping market in long-term it may have a negative impact.

## 3.4 Summary

After the calculation of the correlation of various factors and international dry bulk market, world economy has a high correlation with the dry bulk market, so the world economic development is the primary impact of the international dry bulk shipping market demand. When the world economic has strong incentive, international trade corresponding to rise, along with huge demand for shipping; when the world economy into recession, international trade shrinked, the shortage of cargo will depress the

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<sup>2</sup> “Flattening of the world” this opinion is proposed by Thomas Friedman, in a book called “the World is Flat” which content is to analyze globalization, primarily about the early twenty-first century.

shipping market eventually. Analysis of this issue cannot be considered the cycle of dry bulk market is equal to the cycle of economic market simply, dry bulk shipping market ups and downs is determined by the interaction of demand and supply. In addition, it is necessary to note that the change of structure of commodity in post-industrial era, the economic incident, and the national policy factors should also be in account. Therefore, shipping market cycle is different from and economic cycle, there is certain uniqueness.

## **Chapter 4 Prediction of the Dry Bulk Market Based on the BP**

### **Neural Network**

#### **4.1 Methodology**

##### 4.1.1 Introduction of Data

The paper uses BDI to make a short-term prediction based on BP neural network. From the previous discussion about, BDI called "barometer" of the international dry bulk shipping market, by which it reflects the world dry bulk shipping market's general tariff level, with highly authoritative and representative. So far, BDI has significant guiding in three aspects: reaction extent of shipping freight fluctuation; as the tools of futures trading; as the measure of transaction price. Therefore, the BDI always has been the key indicators of dry bulk market analysis and forecasting, to investment and risk aversion.

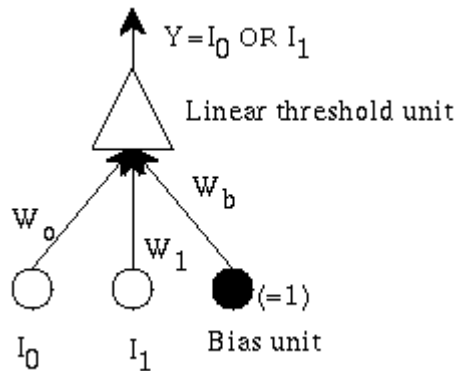
##### 4.1.2 Introduction of the Adaptive Neural Network

On this matter, Smith (2003) stated that:

Neural networks are a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, simple scalar messages and adaptive interaction between elements.

A biological neuron may have as many as 10,000 different inputs, and may send its output (the presence or absence of a short-duration spike) to many other neurons. Neurons are wired up in a 3-dimensional pattern. Real brains, however, are orders of

magnitude more complex than any artificial neural network so far considered. Later, we will use a simple single unit adaptive network as an example.<sup>3</sup>



The network has to 2 inputs, and one output.

All are binary the output is

1 if  $W_0 * I_0 + W_1 * I_1 + W_b > 0$

0 if  $W_0 * I_0 + W_1 * I_1 + W_b \leq 0$

We want it to learn simple OR: output a 1 if either  $I_0$  or  $I_1$  is 1.

Figure 8 A simple single unit adaptive network

Source: Smith, L. (1996) An Introduction to Neural Networks

Back-propagated Neural Network is well-known developments of the Delta rule for single layer networks.

Smith (1996) also researched that:

BP neural network is a development from the simple Delta rule in which extra hidden layers (layers additional to the input and output layers, not connected externally) are added. The network topology is constrained to be feed forward: i.e. loop-free - generally connections are allowed from the input layer to the first (and possibly only) hidden layer; from the first hidden layer to the second,...., and from the last hidden layer to the output layer.

The basic idea of the BP neural network is using the LMS (least means squares) to learn algorithm; using the gradient search technology in the learning process of the network; amendment right to use the error back propagation in order to achieve the minimize mean square error of network's actual output and expected output.

<sup>3</sup> The example from the website: <http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html>

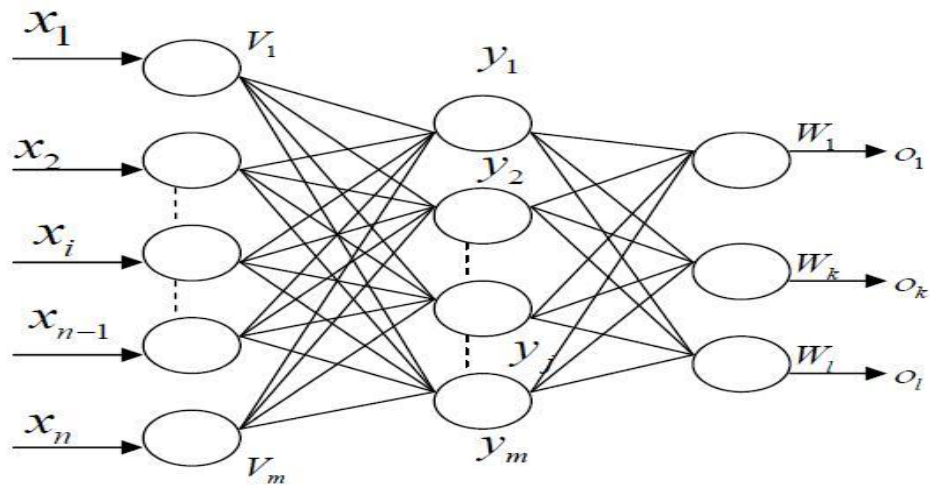


Figure 9 BP net of 3 layers

Source: Crochat, P. & Franklin, D. *Back-Propagation Neural Network Tutorial*

$X = (X_1, X_2, \dots, X_i, \dots, X_n)^T$  is the input vector;  $Y = (Y_1, Y_2, \dots, Y_i, \dots, Y_n)^T$  is the hidden layer input vector;  $O = (O_1, O_2, \dots, O_i, \dots, O_n)^T$  is output layer output vector; the weight matrix between hidden layer to output layer is use  $W = (W_1, W_2, \dots, W_k, \dots, W_i)^T$ , which the column vector  $W_k$  is K-th output layer neuron corresponding weight vector.

In Smith (1996), he has written that:

The hidden layer learns to recode (or to provide a representation for) the inputs.

More than one hidden layer can be used. The architecture is more powerful than single-layer networks: it can be shown that any mapping can be learned, given two hidden layers (of units). The units are a little more complex than those in the original perceptron: their input/output graph is.



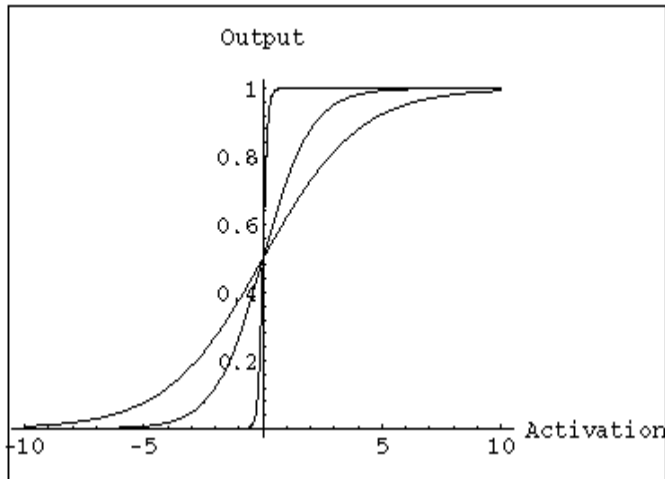


Figure 10 The graph of output

Source: Smith, L. (2003) An Introduction to Neural Networks

Running the network consists of: forward pass (the outputs are calculated and the error at the output units calculated), and backward pass which is the output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

## 4.2 Establish BP Neural Network model

### 4.2.1 Selection of Data

In this paper, a collection of every trading day of the BDI index from 2011.01.04 to 2012.04.25, a total of 327 data. Use of these data based on BDI index of short-term prediction and analysis. In the short term, the BDI index has been relatively stable, more coherence. In this paper, the BDI prediction is the prediction of time series, the input sample is divided into k groups, each group of the first m values as inputs, the m+ 1 data as output data, based on preliminary findings of input data in 7-12 between most can reflect a small shipping market characteristics, after many times experiment, found that when the input data is 10, the network error significantly reduced, so that the optimum input data is 10, choose 1 to 307 groups as sample data ( P ), to construct

As a function:

$$Y = 1 / (1 + \exp(-k \cdot (\sum W_{in} * X_{in})))$$

The graph shows the output for k=0.5, 1, and 10, as the activation varies from -10 to 10.

a neural network and the training of the network. From 308 to 317 were test group (P1), to test the trained network. Based on this principle, for the 10 consecutive trading day of index to predict the next trading day of index, data can be obtained in 317 groups of data, as shown below (figure 11).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	2011/1/4	1693												
2	2011/1/5	1621												
3	2011/1/6	1544												
4	2011/1/7	1519												
5	2011/1/10	1495												
6	2011/1/11	1480												
7	2011/1/12	1453												
8	2011/1/13	1438												
9	2011/1/14	1439												
10	2011/1/17	1439	no											
11	2011/1/18	1432	1	1693	1621	1544	1519	1495	1480	1453	1438	1439	1439	1432
12	2011/1/19	1411	2	1621	1544	1519	1495	1480	1453	1438	1439	1439	1432	1411
13	2011/1/20	1393	3	1544	1519	1495	1480	1453	1438	1439	1439	1432	1411	1393
14	2011/1/21	1370	4	1519	1495	1480	1453	1438	1439	1439	1432	1411	1393	1370
15	2011/1/24	1345	5	1495	1480	1453	1438	1439	1439	1432	1411	1393	1370	1345
16	2011/1/25	1292	6	1480	1453	1438	1439	1439	1432	1411	1393	1370	1345	1292
17	2011/1/26	1234	7	1453	1438	1439	1439	1432	1411	1393	1370	1345	1292	1234
18	2011/1/27	1186	8	1438	1439	1439	1432	1411	1393	1370	1345	1292	1234	1186
19	2011/1/28	1137	9	1439	1439	1432	1411	1393	1370	1345	1292	1234	1186	1137
20	2011/1/31	1107	10	1439	1432	1411	1393	1370	1345	1292	1234	1186	1137	1107
21	2011/2/1	1084	11	1432	1411	1393	1370	1345	1292	1234	1186	1137	1107	1084
22	2011/2/2	1064	12	1411	1393	1370	1345	1292	1234	1186	1137	1107	1084	1064
23	2011/2/3	1045	13	1393	1370	1345	1292	1234	1186	1137	1107	1084	1064	1045
24	2011/2/4	1043	14	1370	1345	1292	1234	1186	1137	1107	1084	1064	1045	1043
25	2011/2/7	1045	15	1345	1292	1234	1186	1137	1107	1084	1064	1045	1043	1045
26	2011/2/8	1064	16	1292	1234	1186	1137	1107	1084	1064	1045	1043	1045	1064
27	2011/2/9	1092	17	1234	1186	1137	1107	1084	1064	1045	1043	1045	1064	1092

Figure 11 Treatment of data

Because the amplitude of different sizes of the raw data, sometimes there is a large difference between the data. Directly put into use, the measurement value fluctuations on the monopoly of the neural network learning process, it does not reflect the small change of the measured value. And practical incentive function tangent of the Sigmoid the output range [0, 1]. Therefore, before the network training, the input data and the target vector to go through the processing of normalization on the 327-group data normalized, rounded to the [0, 1], use the following formula:

$$Y = \frac{(X - X_{min})}{X_{max} - X_{min}} \quad Y \in (0, 1)$$

Finally, the data obtained from an anti-normalized real value, use the following formula:

$$Y = X_{min} + Y(X_{max} - X_{min})$$

#### 4.2.2 Selection of Network Parameter

##### (1) Selection of weight and threshold

The initial value of neural network weights and threshold for network training have a great relationship between whether the model can reach a local minimum, or the convergence of the data and the length of the training time. So, always hope that initial weights after each neuron's output value is close to zero, it can ensure that each neuron weights can be adjusted in their incentive function change of maximum point. In general, the weights and threshold of initial values are chosen between  $[-1, 1]$  random number.

##### (2) Learning rate selection

Learning rate determines each cycle generated by the weight variation. The large learning rate can lead to system instability; small learning rate will lead to a long learning time, the convergence speed may be very slow, but can guarantee the network error value tends to be the minimum error value. So in the general case, should choose a smaller learning rate to ensure the stability of the system. Learning rate range is selected between  $0.01 \sim 0.7$ . For each specific network has a proper learning rate. This paper based on test of the model the learning rate selecting 0.05 after adaptive adjustment.

##### (3) Incentive function selection

Incentive function is a nonlinear, continuous differentiable non decreasing function, can be strictly using the gradient method to calculate its right, learning analytic formula is also very clear. For the multilayer neural network, incentive function on the division of the region is composed of a nonlinear plane consisting of regions, it is relatively soft, smooth any interface. Therefore, this classification is better than linear partition in accurate, reasonable, and fault tolerance. In this paper, after many of the experimental results, the sample data of Sigmoid function to predict the results of optimal tangent.

$$\text{Sigmoid Function: } f(x) = \frac{1-e^{-2x}}{1+e^{-2x}}$$

#### (4) Expected error choice

In the design process of the network training, error should also be compared after training to determine an appropriate value is relative to the needs of hidden layer node number to determine, for relatively small error is to rely on to increase the node of the implicit layer, and longen the training time to get. In the network training process should be based on the actual situation of predetermined error bound. Error bounds of selected solely on the basis of network convergence speed size and specific sample learning accuracy to determine. When expected error Value selection is small, the learning effect is good, but it slows down convergence speed, increasing the number of training. Usually the selected neural network error bounds for 0.0001-0.01, namely in the iterative calculation error value is less than the expected error, is that learning is complete, output the results. Based on the experiment, the expected error finally selected for 0.01.

### **4.3 Prediction of BDI based on BP Neural Network**

#### 4.3.1 The Determination of Network Layer

BP algorithm is very sensitive to network structure; network structure is different between each other. In general, two hidden layer is complex than the network with a hidden layer of network, the more hidden layers the more complex the error back propagation calculation process is, therefore, with one hidden layer in three layer BP network is appropriate choice. This paper's number of implicit layers only to select one layer, then the BP neural network layer includes input layer, hidden layer and output layer.

Hidden layer neuron number can improve mapping precision, but leads to a long learning time, too much the number of hidden layer nodes also reduce the network

generalization ability and training is easy to fall into local minima but not the optimal solution, and also may lead to the weak network fault tolerance and generalization ability. So must be integrated factors in many aspects in the design, to find an optimal number of hidden layer nodes. Generally determine the number of hidden layer nodes of the basic principle is: meet precision down as far as possible, compact structure, namely as little as possible the number of hidden layer nodes. Common hidden layer nodes determine method:

$$1. n_1 = \sqrt{(n+m)} + a$$

$$2. n_1 = \log_2 n$$

$$3. n_1 = \sqrt{(mn)}$$

$$4. n_1 = 2 * n + 1$$

Of which,  $n_1$  is the node of hidden layer,  $m$  is the output number,  $n$  is the input number,  $a$  is a constant between  $[0,10]$ . Finally, the hidden layer node select as 4.

Main code of the model can be seen from Appendix IV.

#### 4.3.2 Predicting Outcomes

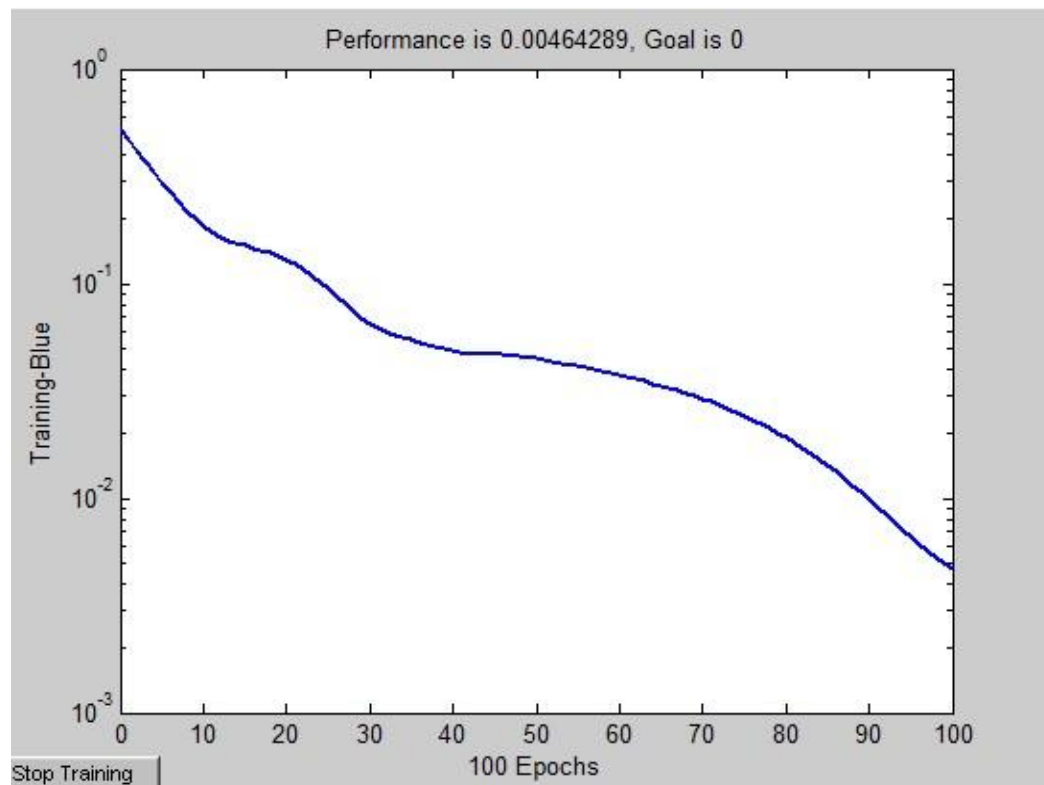


Figure 12 Training performance

Training have reached the expected error is less than 0.01, 0.00464289.

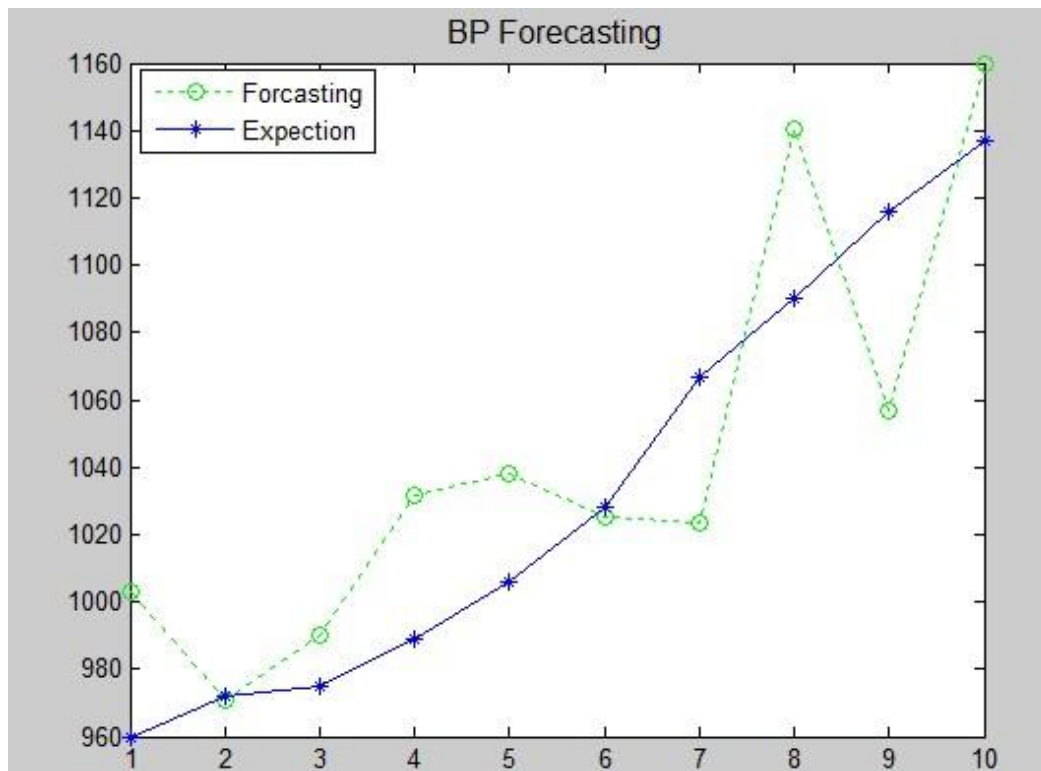


Figure 13 BP forecasting

All the data are shown in the following table.

Table 6 Training result

	Actual value	Predicted value	Error
2012/4/12	960	1003	4.500%
2012/4/13	972	971	-0.100%
2012/4/16	975	990	1.560%
2012/4/17	989	1032	4.300%
2012/4/18	1006	1038	3.210%
2012/4/19	1028	1025	-0.300%
2012/4/20	1067	1023	-4.100%
2012/4/23	1090	1141	4.650%
2012/4/24	1116	1057	-5.300%
2012/4/25	1137	1160	1.990%

Visibly, predictive value and the real worth of error in [-5.3%, 4.65%], the average error is 3%, the trained network forecasting effect is good.

For the next ten days BDI index prediction using the trained network, with 318~327 data to forecast the 328th data, and then from 319 to 328 data to forecast the 329th data, and so on to the next ten trading days of BDI index (figure 14).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
313	2012/4/3	931	303	884	896	902	908	912	917	922	930	934	934	931	
314	2012/4/4	926	304	896	902	908	912	917	922	930	934	934	931	926	
315	2012/4/5	928	305	902	908	912	917	922	930	934	934	931	926	928	
316	2012/4/10	928	306	908	912	917	922	930	934	934	931	926	928	928	
317	2012/4/11	944	307	912	917	922	930	934	934	931	926	928	928	944	
318	2012/4/12	960	308	917	922	930	934	934	931	926	928	928	944	960	
319	2012/4/13	972	309	922	930	934	934	931	926	928	928	944	960	972	
320	2012/4/16	975	310	930	934	934	931	926	928	928	944	960	972	975	
321	2012/4/17	989	311	934	934	931	926	928	928	944	960	972	975	989	
322	2012/4/18	1006	312	934	931	926	928	928	944	960	972	975	989	1006	
323	2012/4/19	1028	313	931	926	928	928	944	960	972	975	989	1006	1028	
324	2012/4/20	1067	314	926	928	928	944	960	972	975	989	1006	1028	1067	
325	2012/4/23	1090	315	928	928	944	960	972	975	989	1006	1028	1067	1090	
326	2012/4/24	1116	316	928	944	960	972	975	989	1006	1028	1067	1090	1116	
327	2012/4/25	1137	317	944	960	972	975	989	1006	1028	1067	1090	1116	1137	
328		1188		960	972	975	989	1006	1028	1067	1090	1116	1137	1188	
329		1143		972	975	989	1006	1028	1067	1090	1116	1137	1188	1143	
330		1185		975	989	1006	1028	1067	1090	1116	1137	1188	1143	1185	
331		1202		989	1006	1028	1067	1090	1116	1137	1188	1143	1185	1202	
332	following	1124		1006	1028	1067	1090	1116	1137	1188	1143	1185	1202	1124	
333	10 trading	1154		1028	1067	1090	1116	1137	1188	1143	1185	1202	1124	1154	
334	days	1213		1067	1090	1116	1137	1188	1143	1185	1202	1124	1154	1213	
335		1210		1090	1116	1137	1188	1143	1185	1202	1124	1154	1213	1210	
336		1085		1116	1137	1188	1143	1185	1202	1124	1154	1213	1210	1085	predicted
337		1172		1137	1188	1143	1185	1202	1124	1154	1213	1210	1085	1172	data
338															
339															
340															

Figure 14 Predicting outcomes

Red data is the prediction data, while the data above the thick line is detective number. The obtained data were after the decimal point, as shown in the figure above, and the next ten trading days of the BDI index: 1188, 1143, 1185, 1202, 1124, 1154, 1213, 1210, 1085, and 1172.

We can make a bold assumption, if there is no impact of the new external emergencies, BDI trend there will be no severe fluctuations in the second half of 2012. With the gradual recovery of the world economy, the weakening of the negative impact of the debt crisis in Europe, the BDI future trend will steadily between 1100 and 1500 with slight concussion.

#### 4.4 Summary

Comprehensive evaluation of the value of international dry bulk shipping market, a comprehensive market factors including freight index, a certain degree of correlation between various indicators in the system, reflect the information to a certain extent

overlap, so it is necessary to identify one or a few less comprehensive index information without overlap, while the amount of information contained in more. In the revision process of BDI index has been covered some indicators of the market evaluation system, which, known as the dry bulk market "barometer", so select the BDI as a forecast index of dry bulk market is reasonable. This section is selected 2011.01.04-2012.04.25 day during the BDI, a total of 327 values to do the prediction of BP Neural Network, get 2012.04.25 after the next 10 days, that is, 2012.04.26-2012.05.05 BDI value.



## Chapter 5 Conclusions

### 5.1 Main Findings

*Firstly, this paper recognized that the development of world economy and international dry bulk market most associated.* Therefore, the world economic development is the most important factor on the impact of the international dry bulk shipping market demand. When the world economic growth, international trade presents growth trend, along with tremendous demand for shipping; when the world economy into recession, generate the atrophy of the international trade, which lead to the drop of the demand in bulk cargo shipping volume , shipping market downturn.

*Secondly, dry bulk shipping market ups and downs is determined by the interaction of demand and supply.* As text mentioned before, due to the shipping market is a trading derivative market, and the trade development level depends on the demands of the world economy, therefore, the shipping market cycle is closely connected with the economic cycle, or we can say that it is actually the economic cycle in the shipping market reflected. The demand of shipping is directly affected by the economic and trade development, while, shipping supply has many characteristics, such as price elasticity of supply is very weak, it increases and decreases obviously hysteresis etc. All these features make the shipping market cycle is different from and economic cycle, there is certain uniqueness.

Thirdly, we made a bold hypothesis, in the second half of 2012, the trend of BDI will tend smooth, if there is no new external contingencies impact. With the gradual recovery of the world economy, and the weakening of negative effects of the debt crisis in Europe, the rising trend of BDI getting stronger. However, from the whole situation to see, autumn winter season is still the main BDI decline season, so index will be steadily between 1100 points to 1500 points with oscillation.

## **5.2 Limitations of Research**

Firstly, when assessing the factor of dry bulk market, the paper simply set the bunker price as the cost of shipping. However, these two aspects vary regarding to different scenarios. For bunker price, considering the port of Singapore is internationally famous supply port, so the use of Singapore harbor 380CST price as a marine fuel price. Among all the factors, marine fuel consumption occupies the fleet operating costs by more than 25%, has become the constraints of fleet management and owner of profit the biggest factor, thus we use bunker price to represent the shipping cost. While, the paper just analyzes which factor has the high relevance with the dry bulk market. Therefore, bunker price can represent the trend of shipping cost relatively.

Backing to question at the very beginning of the paper, “when and why did dry bulk market begin to change?” It much depends on a large amount of data and the model support. Limitation of the resources and ability of math, the paper can just use the grey relational analysis and BP neural network with some qualitative analysis. The result of prediction will have some error, while, the error is less than 3%, is an acceptable answer.

Based on major conclusion we have, we can see that the vicissitude of the dry bulk market is determined by the interaction of supply and demand primarily, with under many related factors.

## Bibliography

Duru, O. (2012). A multivariate model of fuzzy integrated logical forecasting method (M-FILF) and multiplicative time series clustering: A model of time-varying volatility for dry cargo freight market. *Expert Systems with Applications*, 39 (4), 4135-4142.

Duru, O., Bulut, E., & Yoshida, S. (2012). A fuzzy extended DELPHI method for adjustment of statistical time series prediction: An empirical study on dry bulk freight market case. *Expert Systems with Applications*, 39 (1), 840-848.

Dai, W. S., Lv, Q. J., & Pitt, D. (2007, July). Wavelet model for financial time series analysis based on discrete wavelet decomposition and support vector regression. *Statistics and Decision*, 4-7.

Deng Zhidong, Sun Zeng, By Using the Linear It Again Adaptive Variable Step Length Fast BP Algorithm, *Pattern Recognition and Artificial Intelligence*, 1993, 6(4): 319-323

Dong Guanghua, An optimization of the initial value comprehensive global optimization fast BP algorithm, Hefei university of technology academic journal, 2000,23(6): 992-995.

Elliott D L. A Better Activation Function for Artificial Neural Networks [J]. *Technical Research Report*, 1993, 8:1-3.

Fahlman S E. *Faster-Learning variations of back propagation: An empirical study*[C]. Proceedings of the 1988 Connectionist Models Summer, 1988, 38-51.

- Glen, D. R., & Martin, B. T. (2004). A survey of the modeling of dry bulk and tanker markets. *Research in Transportation Economics*, 12, 19-64
- Holland J H. *Adaptation in Natural and Artificial System* [M] America :University of Michigan Press, 1997, 45-56
- Jiang, D. N. (2009). *Research of BDI periodic fluctuation based on BP filter*. Unpublished Ph.D.'s thesis, Shanghai Maritime University, Shanghai, China.
- Kavussanos, M. G., & Alizadeh-M, A. H. (2001). Seasonality patterns in dry bulk shipping spot and time charter freight rates. *Transportation Research Part E*, 37 (6), 443-467.
- Kavussanos, M. G., & Alizadeh-M, A. H. (2002a). The expectations hypothesis of the term structure and risk premiums in dry bulk shipping freight markets. *Journal of Transport Economics and Policy*, 36 (2), 267–304.
- Kavussanos, M. G., Visvikis, I. D., & Batchelor, R. A. (2004). Over-the-counter forward contracts and spot price volatility in shipping. *Transportation Research Part E*, 40 (4), 273–296.
- Karuppiah, J., & Los, C. A. (2005). Wavelet multiresolution analysis of high-frequency Asian FX rates, Summer 1997. *International Review of Financial Analysis*, 14 (2), 211-246
- Köhn, S., & Thanopoulou, H. (2011). A gam assessment of quality premia in the dry bulk time–charter market. *Transportation Research Part E*, 47 (5), 709-721.
- Kirkpatrick S, Gelatt C D, Vecchi M P. *Optimization By Simulated Annealing* [J] Science, 1983, 220:671-680.

- Labat, D. (2005). Recent advances in wavelet analyses: Part 1. A review of concepts. *Journal of Hydrology*, 314 (1-4), 275-188.
- Laulaiainen, R. (2007). Dry bulk shipping market inefficiency, the wide perspective. *Journal of Transport Geography*, 15 (3), 217-224.
- Li, B. & Jiang, W. Chaos optimization method and its application, *Control Theory and Applications*, 1997, 14(4): 613-615.
- Liu, X. J. & Liu, H. *Artificial neural network and the particle swarm optimization*, 2005(92-134) Beijing: Beijing University of posts and telecommunications press
- Li, M. Genetic algorithm to optimize neural network structure and to weight vector, *Journal of Image and Graphics*, 1999 4(6): 491-495.
- Liu, Z.J. (2009) *Research On the Fluctuation and Forecasting of International Dry Bulk Shipping Market Cycle Based On Wavelet Theory*. Unpublished master's thesis, Dalian Maritime University, Dalian, China.
- Lundgren, N. G. (1996). Bulk trade and maritime transport costs: The evolution of global markets. *Resources Policy*, 22 (1-2), 5-32.
- Xu, J. J., Yip, T. L., & Marlow, P. B. (2011). The dynamics between freight volatility and fleet size growth in dry bulk shipping markets. *Transportation Research Part E*, 47 (6), 983–991.
- Stopford, M (2009). *Forecasting developments in the shipping cycle and revenues*. Unpublished material, Clarkson.

- Veenstra, A. W., & Franses, P. H. (1997). A co-integration approach to forecasting freight rates in the dry bulk shipping sector. *Transportation Research Part A*, 31 (6), 447-458.
- Yan, P. F. & Zhang, C. S. *Artificial neural network and simulated evolutionary computation*, Beijing: Tsinghua University Press, 2000, 26-56.
- Wang, L. & Zheng, D. Z. Prior to the network two hybrid learning strategies, *Journal of tsinghua university (natural science edition)*, 1998 38(9): 95-97.
- Tang Wei, Zhang Xueyi, Li Dianpu, *Neural network weights chaos optimization method*, Journal of Harbin Engineering University, 2000, 21(3): 12-15.
- Wu Y S. How to Choose an Appropriate Transfer Function in Designing a Simplest ANN to Solve Specific Problems [J] *Science in China (Series E)*, 1996, 39(4):105-109.
- Wei, J. (2010. September). Ups and downs of international dry bulk market. *Maritime China*, 09, 34-36
- Wang, Y. X., & Liu, S. Z. (2010. April). International dry bulk cargo market prospect in 2010. *Port Economy*. 35-36
- Crochat, P. & Franklin, D. Back-Propagation Neural Network Tutorial. From World Wide Web: [http://pcrochat.online.fr/webus/tutorial/BPN\\_tutorial.html](http://pcrochat.online.fr/webus/tutorial/BPN_tutorial.html)
- Smith, L. (1996, October). An Introduction to Neural Networks. Retrieved April 2, 2003 from World Wide Web: <http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html>

## Appendix I- Initial Data for Grey Relational Analysis

World Seaborne Trade (million tonnes)

Year	Iron ore	Coal		Grain*	Baux/ Alum	Phos. Rock	Minor Bulk	Cont-ainer	Other Dry	Total Dry	Growth ratio
		Coking	Steam								
1999	402	160	298	245	54	33	766	534	910	<b>3402</b>	<b>2.19%</b>
2000	454	171	337	262	54	30	825	598	932	<b>3660</b>	<b>7.58%</b>
2001	483	170	376	260	52	31	845	621	917	<b>3726</b>	<b>1.80%</b>
2002	517	165	394	269	55	30	861	688	975	<b>3920</b>	<b>5.21%</b>
2003	594	166	435	265	60	29	906	773	953	<b>4105</b>	<b>4.72%</b>
2004	664	171	470	273	65	31	973	878	935	<b>4391</b>	<b>6.97%</b>
2005	716	180	492	273	69	31	1011	969	920	<b>4608</b>	<b>4.94%</b>
2006	779	176	527	290	75	30	1084	1076	890	<b>4864</b>	<b>5.56%</b>
2007	841	194	558	302	89	31	1149	1193	832	<b>5127</b>	<b>5.41%</b>
2008	898	199	577	323	94	31	1134	1249	877	<b>5325</b>	<b>3.86%</b>
2009	992	188	590	317	72	20	1035	1127	807	<b>5054</b>	<b>-5.09%</b>
2010	1053	236	662	338	84	23	1159	1275	891	<b>5661</b>	<b>12.01%</b>
2011	1093	223	715	344	98	26	1227	1385	913	<b>5983</b>	<b>5.69%</b>

Bulk and oil trades as per "Dry Bulk Trade Outlook" and "Oil & Tanker Trade Outlook", respectively. LPG trade covers OECD only. 1985-1988 have been omitted

\* Includes soyabeans

Worldwide Bunker Price trends (\$/tonne)

Average	Rotterdam		Singapore		Japan		L.Angeles		Houston	
	380cst	MIDO	380cst	MIDO	380cst	MIDO	380cst	MIDO	380cst	MIDO
1999	93.4	133.0	101.8	141.8	120.2	179.0	96.6	157.8	93.3	143.9
2000	138.4	231.6	158.7	248.5	183.4	287.1	152.1	270.5	136.0	255.7
2001	117.4	192.4	133.1	205.8	160.7	296.0	126.1	256.6	112.8	227.5
2002	133.7	188.2	148.9	197.9	170.6	257.7	142.4	233.6	134.0	196.0
2003	152.9	230.4	172.0	242.5	195.1	276.0	162.1	306.9	160.2	265.1
2004	155.3	313.4	180.3	334.3	214.0	346.6	186.4	398.0	167.3	328.7
2005	234.0	458.4	261.9	481.4	298.4	504.2	263.3	574.4	248.3	508.5
2006	293.0	524.1	313.2	580.6	352.4	591.8	321.0	651.6	303.0	562.3
2007	345.1	571.3	372.8	621.8	418.4	606.0	381.7	709.3	351.8	608.6
2008	471.9	850.7	505.6	907.0	581.0	932.5	524.5	951.5	496.8	933.2
2009	353.8	490.6	371.9	517.9	409.2	557.2	375.1	565.0	360.7	525.0
2010	450.2	667.1	464.1	664.2	518.1	714.8	468.8	721.4	449.3	683.2
2011	617.9	939.6	646.9	932.9	697.0	982.7	655.9	982.4	625.7	969.7



World GDP (% yoy)

Country/Region	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
<b>China</b>	7.3	8.2	8.3	9.1	10.0	10.1	11.3	12.7	14.2	9.6	9.2	10.4	9.2
<b>WORLD</b>	2.2	2.0	2.3	2.9	3.6	4.9	4.6	5.2	5.4	2.9	-0.7	5.2	3.8

World Fleet (million dwt)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
<b>Bulkers</b>	264.1	266.9	274.9	286.9	294.6	301.8	322.1	344.5	357.6	391.7	417.3	458.5	536.1
<b>Combos</b>	15.5	14.8	14.2	13.2	11.8	11.5	10.2	9.4	8.9	8.2	7.9	7.1	8.7
<b>All bulk</b>	<b>279.6</b>	<b>281.7</b>	<b>289.1</b>	<b>300.1</b>	<b>306.4</b>	<b>313.3</b>	<b>322.1</b>	<b>353.9</b>	<b>366.5</b>	<b>399.9</b>	<b>425.2</b>	<b>465.6</b>	<b>544.8</b>

BDI (year)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
<b>BDI</b>	1335	1617	1187	1182	2734	4483	3253	3239	7252	6070	2641	2757	1522

Source: All the data of Appendix I are from the Clarkson SIN 2005.

## Appendix II-1985-2011 Dry Bulk Shipping Capacity and its Growth Ratio

	<b>1985</b>	<b>1986</b>	<b>1987</b>	<b>1988</b>	<b>1989</b>
<b>Capacity</b>	196.9	196.3	195.9	197.6	203.3
<b>Growth ratio</b>	NONE	-0.30%	-0.36%	1.03%	2.88%
	<b>1990</b>	<b>1991</b>	<b>1992</b>	<b>1993</b>	<b>1994</b>
<b>Capacity</b>	211.1	214.4	214.4	218.8	227.5
<b>Growth ratio</b>	3.84%	1.56%	0.00%	2.05%	3.98%
	<b>1995</b>	<b>1996</b>	<b>1997</b>	<b>1998</b>	<b>1999</b>
<b>Capacity</b>	243.1	253.7	263.7	267.9	<b>279.6</b>
<b>Growth ratio</b>	6.86%	4.36%	3.94%	1.59%	4.37%
	<b>2000</b>	<b>2001</b>	<b>2002</b>	<b>2003</b>	<b>2004</b>
<b>Capacity</b>	281.7	289.1	300.1	306.4	313.3
<b>Growth ratio</b>	0.75%	2.63%	3.80%	2.10%	2.25%
	<b>2005</b>	<b>2006</b>	<b>2007</b>	<b>2008</b>	<b>2009</b>
<b>Capacity</b>	322.1	353.9	366.5	399.9	425.2
<b>Growth ratio</b>	2.81%	9.87%	3.56%	9.11%	6.33%
	<b>2010</b>	<b>2011</b>			
<b>Capacity</b>	465.6	544.8			
<b>Growth ratio</b>	9.50%	17.01%			

Source: All the data of Appendix II are from Drewry Shipping Consultants Ltd.

### Appendix III-The main code of BP neural network model

```
Load p p1 t t1;
BP_net=newff(minmax(p),[4 1],{'tansig', 'purelin'}, 'traingdx');
inputWeights=bpnet.IW{1,1};
inputbias=bpnet.b{1};
layerWeights=bpnet.LW{2,1};
layerbias=bpnet.b{2};
net_1.trainParam.show = 100;
net_1.trainParam.lr = 0.05;
net_1.trainParam.mc = 0.9;
net_1.trainParam.epochs = 10000;
net_1.trainParam.goal = 0.01;
BP_net=train(BP_net,p,t);
p1=(p1'-n)/(m-n);
r=sim(BP_net,p1);
r=n1+r*(m1-n1)
display(r)
```