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WORLD MARITIME UNIVERSITY

Malmö, Sweden

**ANN Application in Maritime Industry:
Baltic Dry Index Forecasting & Optimization
of the Number of Container Cranes**

By

CUI HAN

The People's Republic of China

A dissertation submitted to the World Maritime University in Partial
Fulfillment of the requirement for the award of the degree of

MASTER OF SCIENCE

In

MARITIME AFFAIRS

(SHIPPING AND PORT MANAGEMENT)

2012

DECLARATION

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

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

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ABSTRACT

Title of Dissertation: **ANN application in Maritime Industry:
Baltic Dry Index Forecasting &
Optimization of the Number of
Container Crane**

Degree: **MSc**

This dissertation is a study of dry bulk freight index forecasting and port planning, both based on Artificial Neural network application.

First the dry bulk market is reviewed, and the reason for the high fluctuation of freight rates through the demand-supply mechanism is examined. Due to the volatile BDI, the traditional linear regression forecasting method cannot guarantee the performance of forecasting, but ANN overcomes this difficulty and gives better performance especially in a short time. Besides, in order to improve the performance of ANN further, wavelet is introduced to pre-process the BDI data. But when the noise (high frequency parts) is stripped, the hidden useful data may also be eliminated. So the performance of different degrees of de-noising models is evaluated, and the best one (most suitable de-noising model) is chosen to forecast BDI, which avoids over de-noising and keeps a fair ability of forecasting.

In the second case study, the collected container terminals are ranked, and the throughput of each combination (different crane number) is estimated by applying a trained BP network. The BP network with DEA output is combined, simulating the efficiency of each combination. And finally, the optimal container crane number is fixed due to the highest efficiency and practical reasons.

The Conclusion and Recommendation chapter gives some further advice, and many recommendations are given.

KEY WORDS: FORECASTING, WAVELET DECOMPOSITION, ARTIFICIAL NEURAL NETWORK, DATA ENVELOPMENT ANALYSIS, PORT EFFICIENCY

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LIST OF ABBREVIATIONS

AGV	Automatic Guided Vehicle
AI	Artificial Intelligent
ANN	Artificial Neural network
AR	Autoregression
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average model
ARMAX	Autoregressive Moving Average Model with EXogenous inputs model
BCC	Banker,Charnes, and Cooper
BCI	Baltic Capesize Index
BDI	Baltic Dry Index
BFI	Baltic Freight Index
BHMI	Baltic Handymax Index
BP	Back-Propagated
BPI	Baltic Panamax Index
C/P	Charter Party
CCR	Charnes, Cooper, and Rhodes
CCV	central clustering vector
CGT	Compensated Gross Tonnage
CRS	Constant Return Scale
db wavelet	Daubechies wavelet
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DWT	Dead Weight Tonnage
ECA	Emission Control Area
EMA	Exponential Moving Average
GDP	<u>Gross Domestic Product</u>
GHG	Green House Gas

HARPEX	HARPEX Shipping Index
HK convention	Hong Kong Convention
IEA	<u>International Energy Agency</u>
ISL	ISL shipping statistics yearbook
LMS	Least mean square
LNG	Liquid Nature Gas Carrier
MARPOL	International Convention for the Prevention of Pollution from Ships
MATLAB	Matrix Laboratory
MFO	Marine Fuel oil
M-Regression	Multiple-Regression
MSE	Mean Square Error
OECD	<u>Organisation for Economic Co-operation and Development</u>
OLS	Ordinary Least Square
RBF	Radial basis function
SFA	Stochastic Frontier Analysis
SH ship	Second-Hand ship
SSE	Sum of Squared Error
sym wavelet	Symlets wavelet
T/C	Time Charter
TEU	Twenty-foot Equivalent Unit
UNCTAD	<u>United Nations Conference on Trade and Development</u>
VAR	Vector Autoregression
VLOC	Very Large Ore Carrier
VRS	Various Return Scale
WMU	World Maritime University
WTO	World Trade Organization

CHAPTER 1

INTRODUCTION

1.1 Motivation

- Baltic Dry Index (BDI) forecasting

After the financial crisis in 2008, the world economic situation gradually recovered from the extreme downtrend. But in 2011, and the first half of 2012, the regional war, debt crisis, fiscal austerity and the natural disasters result in the development rate slowing down again.

Trade and economies depend on each other indivisibly. And it is known that a 1% downtrend in economies will cause around 10% downtrend in trade.¹ To some degree, trade is the main engine of the economies.

Shipping is derived from international trade, and international trade needs shipping to transport cargo. The main demand countries: Europe, America, and Japan are facing post-crisis depression, performing so weakly. And the biggest exporting country, China, is also carrying out economic reform to change the industry structure. Although in 2010 shipping the sector had a very strong rebound, giving people hope, the next 2 years seemed to break people's hope again. Shipping has returned to a low-cycle, and shipping lines, ship owners are suffering from low freight rates. Many small ship building yards, even worse, are closing due to bankruptcy. During 2002-2008, many banks flooded into the shipping financial market for investment or speculation, but now shipping is the last industry that they are interested in. Recently some Banks claimed they quit shipping finance definitely due to the extremely bad performance. Besides, regulations and new laws came into force, for

¹ See REVIEW OF MARITIME TRANSPORT 2011 (page 4). UNCTAD

example, the arrest of ships, and the GHG emission control, affecting the margin of profitability. In conclusion, it is a tough time for shipping but where there is crisis, there is opportunity. So forecasting will play a very important role in the coming years because people want to survive and grow in the uncertain time.

- Port planning

The port sector plays an important role in the economic development of the whole country, connecting the shipping industry to inland transport. In addition, the maritime container industry, as a predominant mode of inter-continental cargo traffic, has been developing significantly. In order to achieve a better efficiency by adopting economies of scales, the size of container ships has been enlarged by several times in the last several decades. Accordingly, the port, as the connection, has to adapt to the dramatic change of container ships, to meet the increasing demand. But for new ports, especially for those pioneer ports, there is no existing example of port planning, which is involved in huge investment/risks. Besides, the competition between ports has become more and more fierce, focusing on cost-efficiency, time-keeping, and throughput. So appropriate port planning can save a lot in both investment and time.

1.2 Goal

By applying Artificial Neural network, it is intended to forecast the future trend of BDI in the first case study, and obtain the optimal crane number in the second case study.

1.3 Objectives

Due to the two different case studies, there are two separate objectives but based on the same technology: Artificial neural network.

- The Baltic Dry Index forecast

As is known, the dry bulk market is full of uncertainty, the BDI was 17000 high in June of -2008, but fell to 900 low in November after the “free fall”. The high fluctuation will result in high risk for shipping companies and other organizations, but this can be controlled by appropriate forecasting, helping people avoid losses and

improve profitability.

- Port planning optimization

With the development of containerization, the port, as the interface of sea and inland transport has to face increasing demand and competition. So expansion becomes a good choice, but the expansion of a port requires huge investment, which will involve investors in high uncertainty and risk. So combination method is developed to measure the efficiency in order to seek the optimal combination of crane number in port planning.

1.4 Structure of the dissertation

The dissertation consists of Introduction (Motivation, Goal, Objectives, and Structure), Literature review (Dry Bulk market, Forecasting, and Data envelopment Analysis), Methodology (Artificial Neural network, Data Envelopment analysis, and wavelet transformation), Case study 1: Forecasting Baltic Dry Index, Case study 2: Optimization of number of container crane, and Conclusion and Recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Dry Bulk Market

2.1.1 The development of contemporary shipping industry

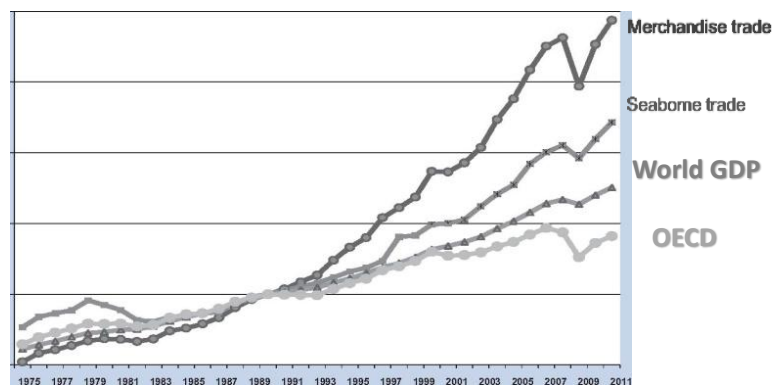


Figure 2.1 Indices for world GDP, the OECD Industrial Production Index, world merchandise trade and world seaborne trade (1975–2011) (1990=100)

Source: *Review of Maritime Transport 2011*, UNCTAD

Since 1950, World exports have grown on average 2.4 times faster than world GDP. As we know, GDP growth depends on industrial production, and trade is driven and affected by GDP. From Figure 2.1, the gap between trade and GDP has become wider. The main reasons are globalization, which improves manufacture and service, including transportation. Recently, the developing and transition economies have played a more and more important role in merchandise trade. If we look at the proportion of these economies, in 1997, they accounted for 34% of the global merchandise trade, but in 2007, it became 40%. No doubt, these countries, BRIC countries² are new emerging powers, and will continue take away a share of the trade from the OECD countries.

² BRIC countries mean Brazil, Russian, India and China.

Ninety% of international cargo volume is transported by sea because shipping is the best cost-efficient way to carry the huge volume of cargo over long distances. Although high value cargo is mostly carried by plane or train, the value proportion of sea transport is growing gradually. In Figure 2.1 , we can find that seaborne trade is still dominated by raw material, intermediate products, and finished products, which all had a strong rebound in 2010. Although in 2011, and 2012*, the world economies slowed down, affecting the recovery of the seaborne trade. In the long term, it will continue to grow, with shifting trade patterns from higher labor cost countries to comparative low labor cost countries.

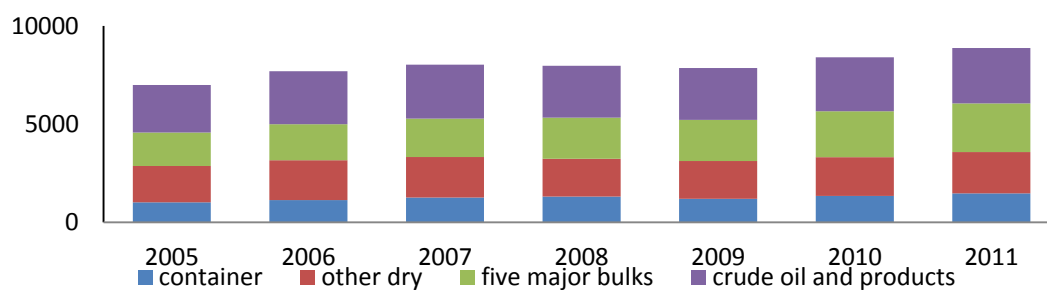


Figure 2.2 Illustration of international seaborne trade from 2005 to 2011, Millions of tons loaded

Source: *Review of Maritime Transport 2011*, UNCTAD and various data

2.1.2 The current issues influencing shipping

When we look at shipping, it is a mixture of cost, benefit, environment, regulation, safety and security. Shipping is not only affected by the whole economic situation, but also reshaped by many other emerging issues. For example, the high bunker price, the new regulations about cutting CO2 emissions, and piracy.

- The bunker price and slow steaming

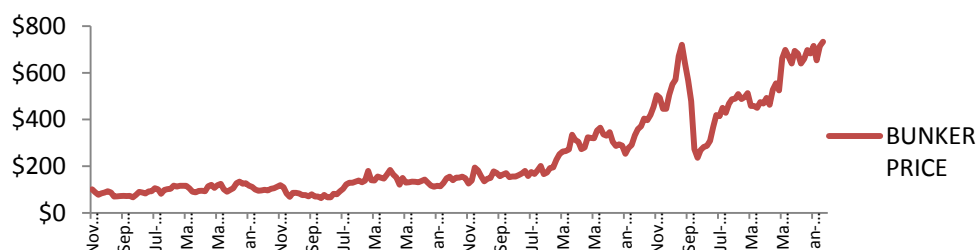


Figure 2.3 World MFO 380 bunker price from 1992 to 2012

Source: Data collected from *Shipping Statistics yearbook 2011*, and www.bunkerindex.com

With the development of the world, the imbalance between oil demand and supply is becoming more and more unstable, and “The IEA estimates that some \$60 billion must be invested in global oil production capacity every year in order to meet global demand³”. In shipping, the cost of bunker accounts for 60% of the operating cost, undoubtedly, the rise of bunker prices will affect the transport cost, finally paid by clients. Since 2004, the era of cheap oil ended, and its price began to rise together with the trade volume. Some studies show: altering the oil price will affect the freight rate in the short term, but in the long term, it will change the trade pattern.

In order to deal with the high oil prices, many shipping companies have decided to use slow-steaming since the financial crisis. The direct effect is cutting down fuel consumption because $\text{fuel consumption} \propto \text{speed}^3$. At the same time, slow-steaming, which absorbs the overcapacity due to the slower speed, will result in a need for more ships in the route to keep the service. In addition, it will cut down emissions. But it also generates more transit time.

We cannot subjectively say that slow-steaming is 100% good for shipping because different ships, routes, and cargoes will lead to different answers. However, as a direct, reactive response to the fragile freight and high bunker prices, slow-steaming makes sense.

- The emission-control regulation and climate change

No doubt, MARPOL73/78 Annex VI, concerning NO_x, SO_x, and Ozone depleting substances has already begun to control the harmful emissions. The new ECA will extend to the U.S. and Canada apart from the original Baltic and North Sea areas.⁴

Roughly, the global shipping industry accounts for 3% of CO₂ emissions. And so far, many proposals are submitted concerning cutting down emissions, including

³ Retrieved from IEA website
<http://www.iea.org/publications/worldenergyoutlook/pressmedia/quotes/23/>

⁴ IMO. North American ECA. Retrieved from
<http://www.imo.org/mediacentre/pressbriefings/pages/44-marpol-amends.aspx>

operational, design, and market-based frameworks. It is very important to make the shipping industry aware of the social responsibility, which can push new regulations on the “lazy shipping companies and ship owners”. With climate change, the sea level will rise, many ports will have to modify their infrastructures and even some trade patterns will significantly change.

However, as the icecap increasingly melts, arctic navigation will no longer be an “impossible mission”. For example, in the last year, around 30 vessels passed the arctic area together with ice breakers in the summer time. It is still a long way to explore the new route, not only about the geographical restriction, but also about the matched assisting industries: ship design, class, regulation, and insurance. Besides, controlling pollution in the fragile polar area is also a big issue.

The regulation will force shipping companies to spend more money on caring about environment, but in the long run, people cannot survive without sustainability, let alone the shipping.

- Piracy, Maritime security

In the last several years, many piracy cases have occurred off the coast of Somalia. And in 2009, 600 nm away from Mogadishu, pirates carried out the attacks. It seems like a pincer to pinch global shipping due to the crucial important position. For crews, their lives and property are severely threatened. For shipping companies, they have to pay more for insurance, manning costs, safe guards, and equipment, if they want to transit this area. Alternatively, if they decide to avoid this area, it will increase the bunker, hire. Of course, all increased cost will be passed to the shipper through higher freight rates.

Now, shipping is in a downtrend with negative profit, so actually, the frequency of the service in a specific route is maintained at a low level. But if one day demand for maritime transport picks up, what will piracy cost? It is always better to cure earlier than later.

2.1.3 Overview of the dry bulk market

Dry bulk transportation plays an important role in the global shipping market,

accounting for approximately 33% of the total sea transportation volume. With the container ship rising up, the general cargo ship, the representative of “low-handling efficiency, high cargo damage rate” has gradually faded out from the major shipping routes. But compared with the rapid declining of general cargo ships, the dry bulk cargo ships are still expanding because the major dry bulk cargo are mostly low-value, huge-volume, long-distance, crucial raw materials of manufacture, infrastructure, and energy, which cannot be substituted. In 2009, the total volume of dry cargo was 5.2 billion tons, and in 2010, it rose to 5.7 billion tons.⁵

- The components of the dry bulk market

The dry bulk market is a combination of the shipper, carrier, and dry bulk cargo. Historically, the shipper was the carrier, even the captain, to carry their own cargo. Although a few extremely strong cargo owners begin to develop their own fleets to carry their own cargo, most of the dry bulk shipping is done in the form of chartering due to various reasons.

Chartering contains time chartering, voyage chartering, contract of affreightment (a little similar to voyage charter) and bareboat chartering. The different forms of chartering mean different cost sharing schemes.

Table 2.1 Cost sharing scheme

	Bareboat	Time charter	Voyage charter
Capital cost	Owner	Owner	Owner
Operation cost	Charter	Owner	Owner
Voyage cost	Charter	Owner	Flexible

Source: Shuo Ma (2011). *Maritime Economics*. (Page 118). World Maritime University.

In dry bulk shipping, Voyage chartering (V/C) and Time Chartering(T/C) are both popular. In V/C the ship owner will pay for all the expenses except the cargo handling cost (flexible), carrying the cargo from port A to port B, and finally charge the shipper the freight. The freight is based on the amount of the cargo they negotiated in advance

⁵ Review of Maritime Transport 2011. UNCTAD.

in the C/P.

Another popular charter is Time-Charter: the charterer will use the ship not necessarily for performing a particular voyage but for a fixed period of time. And in return, the charterer will pay the ship owner the hire. At the same time, the charterer has to carry the burden of the bunker cost. Bareboat Charter is similar to T/C.

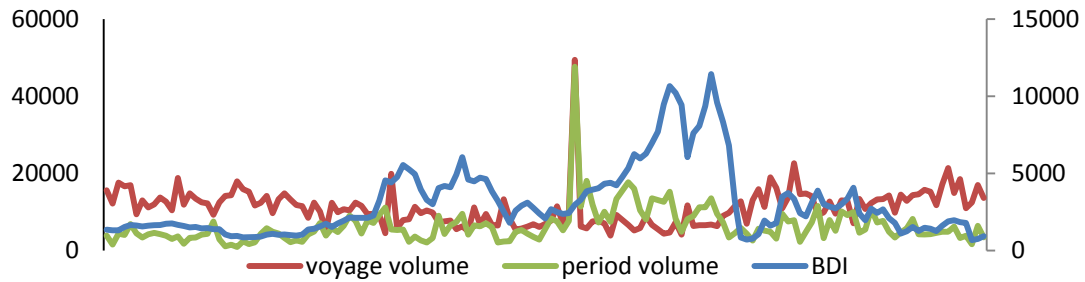


Figure 2.4 Volume of voyage chartering and time chartering Vs. BDI

Source: data collected from. *The Drewry Monthly* (1999-2012). Drewry Shipping Consultant.

Table 2.2 Correlation between BDI, Voyage Volume and Period Volume

	BDI	voyage volume	period volume
BDI	1		
voyage volume	-0.4535	1	
period volume	0.429304	0.196997436	1

This is the correlation among BDI, T/C volume, and Voyage charter volume. BDI vs V/C is negative, but BDI vs T/C is positive. This is because when BDI gets higher and higher, charterers will tend to T/C a ship in order to get a relatively low hire rate, but when BDI is dropping, the charterer will try to V/C or short T/C a ship so as to finish the contract to get a lower freight rate in the downtrend.

- The structure of the dry bulk market

The dry bulk market is close to a perfect competitive market.

The ship owner may be a very strong regional leader or a single-ship company, and the charterer maybe a big importer/exporter or a small sub-charterer company. Both sides constitute the basic demand and supply mechanism. In present times, with the

help of modern communication, the information flow between demand and supply can be easily exchanged, even in international business. If a shipper wants to send a cargo to a specific port at a specific time in a specialized ship, the requirement can be spread to most ship owners` ears quickly.

Most shipping lines are rather strong and control several routes and ports. In contrast, due to relatively low standard of entering, a lot of people flood into the dry bulk market, with a loaned ship and several crews. Most companies in the dry bulk market are rather small. At the same time, consolidation for those companies is not an easy thing because of the number of companies, and their small size. But we should also notice that a lot of political influence and man-made interference will affect and control the market. For example, before the 2008 collapse, one strong company chartered a large number of bulkers, and held them not to put them in the market resulting in a shortage of supply, and freight rates went up at once. So we can define the dry bulk market as very close to a perfect competitive market, but not.

In a perfect competitive market, the price is determined by the balance of the demand and supply. In the dry bulk market, the freight reflects the relationship between demand and ship supply.

- The 5 major dry bulk cargo

According to the types and volume of the dry bulk cargo, we can classify them into 5 major bulks: Iron ore, Coal, Grain, Bauxite/Alumina, and Phosphate.

First, in many countries, coal is the major source of energy, called “steam coal”. The other kind of coal is “thermal coal”, which is mainly used in the production of steel.

Obviously, iron ore and coal are strongly related, and in many cases, the trend of iron ore and coal shipments are rather similar, which is decided by the major producer and exporter due to the imbalanced distribution of natural resources. From 1984-2010, the annual growth of iron ore and coal were both 5%, especially the share of iron ore within the 5 major dry bulk cargoes rose from 36.8% in 1984 to 42.3% in 2010. We have to mention that China, as the biggest developing country, is expanding its infrastructure to satisfy the booming domestic demand. Although China is changing the industry structure under the recession of the financial crisis, the huge population

and urbanization will continue to stimulate the growth of the two major cargoes. Besides, other emerging countries like India, Brazil, and Russia will also maintain the continuous growth with the same demands, which will support the long-haul dry bulk cargo transport. The major carriers are Panamax, Capesize, and VLOC vessels. Second, grain is mostly affected by the weather. However, other factors are also give pressure upon the volume, structure and patterns of grain shipments. There are 4 major influences (a) the shift in demand and usage (e.g. industrial purposes vs. feed); (b) environmental and energy policies that promote the use of alternative energy sources such as biofuels; (c) the evolution in consumption and demand patterns (e.g. higher meat consumption in emerging developing countries leads to more grain shipments for feedstock); and (d) trade measures aimed at promoting or restricting trade flows⁶. The major exporters are Argentina, Australia, Canada, the European Union and the United States, but the major importers are the European Union, Russia, Asia, and Africa, which are mostly developing countries. The long distance between those countries gives the bulk carrier employment. The trade of grain will have an impact on the handymax and handy vessels.

Third are Alumina and Phosphate; Alumina is the major raw material of industry. Experiencing the decline of 2008, the export and import of Alumina rebounded, indicating the recovery of the industry. Another reason, also related to the emerging developing countries, is that stimulus funding and rapid pace of industrialization increases consumption. For Phosphate, because it is the raw material of the compound fertilizer, grain exporters are the major buyer. In 2011, the export remained steady reflecting further consolidation in the economic recovery and demand for grains. But expansion in Russia and Asia may cause a new round of price competition, affecting the shipments. The major carriers are handymax, handysize vessels.

2.2 Forecasting

2.2.1 The shipping market cycles

Before reviewing forecasting, the foundation of the decomposition: shipping cycles,

⁶ Review of Maritime Transport 2009 (Page 34). UNCTAD

which is strongly related to forecasting, is introduced.

“In the fifty-year period following the Second World War, the seven dry cargo freight cycles were shorter, averaging 6.7 years each.”⁷ – Martin Stopford.

Researchers have studied the shipping market cycles, for example, Stopford. He thinks that a shipping market cycle can be dismantled into 3 components: Long shipping cycles, short cycles, and seasonal cycles.

- For the **long cycles**, it is thought that they are driven by technical innovation, economic development or regional change. In other words, these factors give the cycles a backbone, although it is not easy to detect.
- For the **short cycles**, it is easier to identify the periodical stages. “The short cycles shot up and down, and are easy, indeed conspicuous to see.”⁸ We can take China for example. After the 9/11 attacks, industry production in Europe and the U.S. declined, and hire and freight went down accordingly. But since 2002, China, due to entering the WTO in 2001 and reducing the trade barrier, is moving into a high speed development era. In particular, steel production is booming to feed the high speed expansion. So the market should have been weak in 2007, but the Chinese factor supported the market to extend to 2008 after the Beijing Olympics, and free drop from the peak.
- For the **seasonal cycles**, it happens very frequently, with repeating similar fluctuations in consecutive years. For example, Chinese New year, varying from January to February, has a strong impact on the container ship market, because people in Asia will celebrate this festival rather than continue working in the factories, which will definitely cause a decrease in manufacturing and decline of container transport. Another example, in the winter of the northern hemisphere, people there will need more heating, causing more importing of coal and oil, which will push up the bulk market temporarily.

From the statistics, in the last 50 years, the average shipping cycles are 8 years, varying from 5 years to 9 years, but no two cycles are similar. From Stopford’s theory,

⁷ Martin Stopford (2009). Maritime Economics (page 118)

⁸ Martin Stopford (2009). Maritime Economics (page 96)

he divides the cycles into 4 kinds:

Table 2.3 Shipping market fundamental analysis

	Demand growth	Supply growth
Prosperity	Very fast	Shortage
Competitiveness	Fast	Expansion
Weakness	Fast	Overcapacity
Depression	Falling	Overcapacity

Source: Martin Stopford (2009). *Maritime Economics* (3rd edition)

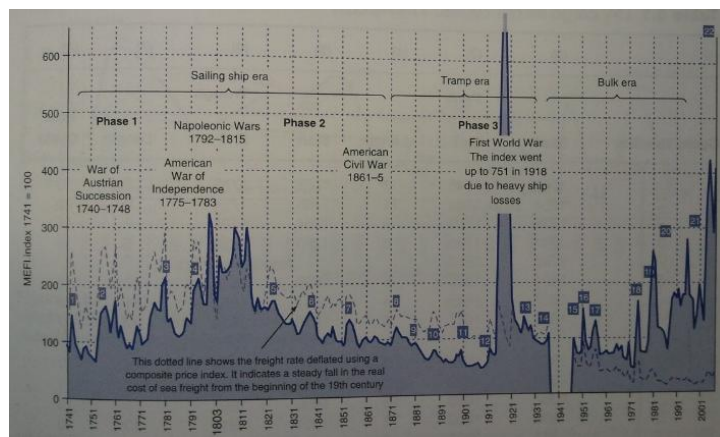


Figure 2.5 Dry Bulk cycles 1741-2007

Source: Martin Stopford (2009). *Maritime Economics* (3rd edition).

Normally, the freight rates are decided by the demand-supply model, but in the shipping market, the demand is inelastic, meaning some kinds of cargo cannot be transported by other substitutes. The lead time of ship building also means that fast-growing demand cannot be satisfied at once, and the long process of ship recycling blocks technological updating. Besides, many ship owners tend to invest in new ships in the prosperous market, not considering the uncertainty and overcapacity but the expectation of high freight. And if we come into details of the market, we have to face the massive relations among the new-building market, scrapping market (the first 2 markets will be strongly affected by the steel price, which is related to iron ore and coal,.), the second-hand market (mainly decided by the expectation of the freight), the world trade volume (following the international trade, driven by global economy,).

and definitely the freight market (we can call it lever).

Sometimes, other than the factors above, an unexpected shock will also lead the market into different directions. For example, the oil crisis, the Suez Canal closing, and the 9/11 attacks. Because of these shocks, the market will develop in an uncertain direction, with huge fluctuation.

2.2.2 The definition of forecasting

Forecasting is the process of making statements about events whose actual outcomes (typically) have not yet been observed. A commonplace example might be the estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term. Both might refer to formal statistical methods. Finally, forecasting will help people make practical decisions.

For most shipping investors forecasting plays a very important role in the whole business. It is how they earn their living. No matter whether they decide to buy a new ship/second hand ship, or choose a certain kind of charter, the more precisely they predict the future, the more profit they will earn. This not only includes the ship owners and shipping companies who are making the prediction, but also bankers who will decide to finance the ship, shipyards who will update the design, engineering companies who are selling the ship equipment, rating agencies who will evaluate the risk, the port authority which needs to follow the newest trend to develop their facilities, forecasting can give a more accurate future to help them to be a better position.

Maritime forecasting is part of economic forecasting. We should see that the shipping market is an extremely complicated market, which is decided by a mixture of 4 basic factors. They contain economic and trade factors, regional regulations and political reasons, influence from upstream and downstream markets, and some unexpected shocks. So it is more complex to forecast the shipping markets.

Historically, shipping forecast has had a poor reputation. If we look at the forecasts made in the 1960s and 1970s, most of them failed, few succeeded. This is especially true for long-term forecasting because people will ignore some little clues resulting in

missing the huge influence later. Although the unpredictable elements always exist in the shipping markets, people are still eager to forecast the future. For example, when the future of the market is not clear, the investors will employ people to forecast the cargo volume, the fleet capacity, and so on. But when the forecasting result comes out, who can say this is 100% right?

Except the bad record of forecasting, when we are forecasting, it is essential to identify the goal, and collect the correct information. Shipping investors know that they are not playing with certainty, but just due to the uncertainty, making the whole shipping game meaningful. With the accumulation of experience, the investors or forecasters can narrow down the possibility, making the right decision, although they have made a lot of wrong decisions before. In addition, the right information can lead the decision-maker through the unclear future, reducing the risk.⁹

2.2.3 The main forecasting methods in the dry bulk market

- The goal of forecasting

Everything occurring in the dry bulk market can be forecasted, but there are three dominant goals. Of course, except the 3 major goals, we also can forecast the bunker price, and crew market situation.

- Forecasting the cargo volume

Cargo volume forecasting is demand forecasting. It contains cargo flow volume (Tonnage x distance), structure of the cargo flow, source and distribution of cargo flow. In this system, we should consider comprehensive information from the global view, combined with the development of global economics and trade.

- Forecasting the capacity of fleet

This is the opposite of cargo volume forecasting. When we consider these questions, many factors will affect the capacity, including average speed, average haul, efficiency of port handling facilities, and the level of management. Besides, delivery of new building ships, scrapping of the old ships, and lying up of ships also will affect the supply of shipping markets.

⁹ Martin Stopford (2009). *Maritime Economics* 3rd edition, page 697-702

■ Forecasting the freight rate

This is the most complex part of the forecasting. In reality, the demand and supply will change dynamically, causing the freight, as the representative of the market to fluctuate.

● The method of forecasting

Generally speaking, we can categorize the forecast models by nature: they are qualitative model, quantitative model, and combination model. Examples of qualitative forecasting methods are: informed opinion and judgment, the Delphi method, market research, historical life-cycle analogy. Examples of quantitative forecasting methods are: last period demand, simple and weighted moving averages (N-Period), simple exponential smoothing, and multiplicative seasonal indexes.

Table 2.4 Summary of Forecasting methods

Time-series forecast	Moving average
	Weighted moving average
	Exponential smoothing
	Autoregressive moving average (ARMA)
	Autoregressive integrated moving average (ARIMA), e.g. Box-Jenkins
	Extrapolation
	Linear prediction
	Trend estimation
	Growth curve
Causal / econometric forecasting methods	Regression analysis
	Autoregressive moving average with exogenous inputs (ARMAX)
Judgmental methods	Composite forecasts
	Statistical surveys
	Delphi method

	Scenario building
	Technology forecasting
	Forecast by analogy
Artificial intelligence methods	Artificial neural networks
	Group method of data handling
	Support vector machines
Other methods	Simulation
	Prediction market
	Probabilistic forecasting and Ensemble forecasting

Source: various sources

The most commonly used methods are moving average, single/multiple regression, ARMA and its extension, VAR. There are several brief introductions of common-used forecast models.

- The moving average

This method shows that the latest data affects the next data mostly. The importance of the previous data affecting the next data will decrease with the increasing interval between those two data. The extent may vary from linear to exponential, depending on which kind of moving average is applied.

This is the formula of weighted moving average.

$$WMA_M = \frac{np_M + (n-1)p_{M-1} + \dots + 2p_{(M-n+2)} + p_{(M-n+1)}}{n + (n-1) + \dots + 2 + 1}$$

n is the weight of p_M, (n-1) is the weight of p_{M-1}, and so on.

This is exponential moving average. The weighting for each older datum point decreases exponentially, never reaching zero.

$$S_1 = Y_1$$

$$t > 1, S_t = \alpha \times Y_t + (1 - \alpha) \times S_{t-1}$$

Y_t is the value at a time period t.

S_t is the value of the EMA at any time period t.

The coefficient α represents the degree of weighting decrease, a constant smoothing factor between 0 and 1. A higher value of α discounts older observations faster.

The moving average is a very convenient way to smooth the data and roughly forecast the trend. It does not apply to that if the data is increasing or decreasing dramatically because the average data is worked out restricted in the past data, impossible to break the limitation. If seasonal cycles exist, the number of items should be roughly equal to the seasonal cycles, otherwise this method cannot eliminate the seasonal cycles.

- Regression analysis

This method mainly focuses on the relationship between the dependent variable and single/multiple independent variables. When we apply regression analysis, the data must satisfy three checking conditions.

This is an example of single regression.

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad i = 1, \dots, n.$$

Y is dependent variable, x is independent variable, β_1 and β_2 are coefficients, and ε is residual, which is the difference between the value of the dependent variable predicted by the model.

One method of estimation is ordinary least squares. This method obtains parameter estimates that minimize the sum of squared residuals, SSE.

$$SSE = \sum_{i=1}^N e_i^2.$$

Minimization of this function results in a set of normal equations, a set of simultaneous linear equations in the parameters, which are solved to yield the

parameter estimators $\hat{\beta}_0, \hat{\beta}_1$

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \quad \text{and} \quad \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

where \bar{x} is the mean (average) of the x values and \bar{y} is the mean of the y values.

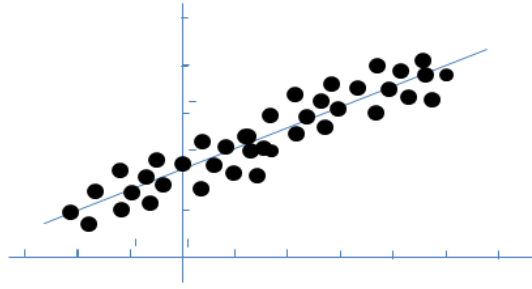


Figure 2.6 Illustration of Regression analysis

In the more general multiple regression model, there are p independent variables:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i,$$

Where x are independent variables, and y is dependent variable, ε is also the residual.

Generally speaking, when modeling a simple thing, single regression is more appropriate than multiple-regression, because the estimation of coefficient and selection of corresponding curve is much easier. When it comes to a complicated model, the single/multiple regression will not be so competent. The ability of fitting and generalization will be restricted, especially when the data is not following a pastime repeating, simple and regular pattern.

- Auto-regression and Auto-regression-moving-average

Autoregressive (AR) model is a type of random process which is often used to model and predict various types of natural phenomena. The autoregressive model is one of a group of linear prediction formulas that attempt to predict an output of a system based on the previous outputs.

$$X_t = c + \sum_{i=1}^p \varphi_i X_{t-i} + \varepsilon_t$$

where $\varphi_1, \dots, \varphi_p$ are the parameters of the model, c is a constant (often omitted for simplicity) and ε_t is white noise.

ARMA is the combination of AR and MA, sometimes called Box–Jenkins models after the iterative Box–Jenkins methodology usually used to estimate them, are typically applied to auto-correlated time series data.

The notation ARMA (p, q) refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR (p) and MA (q) models

$$X_t = c + \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i}.$$

where the $\theta_1, \dots, \theta_q$ are the parameters of the model, μ is the expectation of X_t (often assumed to equal 0), and the $\varepsilon_t, \varepsilon_{t-1}, \dots$ are again, white noise error terms.

ARMA is appropriate when a system is a function of a series of unobserved shocks (the MA part) as well as its own behavior. For example, stock prices may be shocked by fundamental information as well as exhibiting technical trending and mean-reversion effects due to market participants.

2.2.4 The ANN-based forecasting methods

- Artificial Neural Network

D.V. Lyridis (2004) applied ANN in different lags¹⁰ to forecast the market and it gave better performance than M-regression model. He got several useful conclusions to help people to construct ANN.

Başak introduced a special trend factor into the input variables, which follows the classical supply-demand model, showing a combination of demand-supply theory and ANN.

Wang Dong (2009) gave some good advice in selection of neuron number in hidden layer, and functions.

- Combination of artificial neural network and other methods

Jiang Pengfei and **Cai Zhihua** (2007) employed a combination of RBF network and genetic algorithms, which improve the performance of RBF network.

Athanasios V. Voudris (2005) used various parameters, not restricted in the demand and supply to train BP network based on the genetic algorithms to improve the performance.

JV Hansen* and **RD Nelson** (2003) showed that by applying decomposition, the ANN can give better performance than that of the classical decomposition.

¹⁰ 1 month, 3 months, 6 months, 9 months and 12 months

Hu Junsheng and **Xiao Dongrong** (2005) combined wavelet package with BP network to forecast the economics, which shows better performance than that by pure BP network.

Niu Dongxiao and **Xing Mian**(1999) gave the research of forecasting the non-linear data based on wavelet-ANN model in order to avoid the inherent defect of BP network.

Generally speaking, linear model is suitable for simple-relation, long-trend forecasting, but when it comes to non-linear and high fluctuating data, it can do nothing. Due to the special architecture of ANN, it usually has better performance than a regression model in the non-linear data. In addition, with the help of other technologies, it can be built, trained smarter, and gives even better results.

2.3 Data Envelopment Analysis

Table 2.5 Literature review of various DEA-based Models

Author	Method	Units	Inputs	Outputs
Angela Stefania Berantino and enrico Musso(2010)	SFA and DEA	30 terminals	Dimension of quay, number of terminals, area of the port for handling, handling equipment	Variable selections
Tao Chen(2010)	DEA-Regression	140 terminals in China	Quay length, TT density, Operation years, load M40	Quay efficiency
Cullinane and Wang(2006)	DEA-CCR and BCC	67 European ports	Quay length, area, equipment	Container throughput
Cullinane et al.(2005)	DEA-CCR,BCC and FHD	57 international ports	Quay length, quay cranes, yard gantries, straddle carriers	Container throughput

Barros and athanassiou(2004)	DEA-CCR,B CC	2 Greek and 4 Portugal ports	Labour and capital cost	Freight, cargo throughput, container throughput, number of ship
Tongzon(2001)	DEA-CCR	16 ports	Number of Crane, tug, terminals, delay, labour	Throughput, ship working rate
Martinez-Budria et al.(1999)	DEA-BCC	26 Spanish ports	Labour expenditures, depreciation charges, other expenditure	Cargo moved in docks, revenue from port facilities.
Roll and Hayuth(1993)	DEA-CCR	Hypothetical 1 numerical example of 20 ports	Manpower, capital	Cargo throughput service level, consumer satisfaction, ship calls

We can find that researchers use different parameters to measure the efficiency or productivity. In most studies, Data Envelopment Analysis (DEA) was widely used to quantify the relationship between the outputs and inputs and different terminals are ranked in terms of “efficiency”. But the controversy between ship operators and port operators concerning the target is still going on. The selection of the output depends on the aim of the research. For example, one port may have high **quay productivity** preferred by the port operator (achieved by deploying dense cranes to each quay), but the shipping lines may be in favor of high **quay crane efficiency**. For this case study, the target is to seek the best efficiency of the terminal.

CHAPTER 3

METHODOLOGY

3.1 Artificial Neural Network

3.1.1 Introduction of artificial neural network

Artificial neural networks are, as their name indicates, computational networks which try to simulate, the performance of neurons in the human brain. This simulation is a gross neuron-by-neuron or element-by-element simulation. It absorbs the principle from the neurophysiological knowledge of biological neurons and of networks of such biological neurons. It is different from conventional computing technology that serves to replace, enhance or speed-up human brain computation without considering the organization of the basic elements and of the network. It belongs to “Artificial Intelligence” (AI), which includes all research aimed to simulate intelligent behavior. Artificial neural networks are the major research at present, containing many different disciplines. Methods contributing to this research consist of biology, computing, electronics, mathematics, physics, and economics. The approaches to this target contain a lot, but the general idea is to adopt the knowledge of the nervous system and human brain to design intelligent artificial systems.

The biological neural network contains neurons, which include the neuron`s dendrite, nucleus, soma, axon and axon terminal. Neural activity passes from one neuron to another in terms of electrical triggers which transfer from one cell to the other down the neuron`s axon, by the electrochemical process of voltage-gated ion exchange along the axon and diffusion of neurotransmitter molecules through the membrane over the synaptic gap. The axon can be considered as a connection wire. However, the mechanism of signal flow is not via electrical travelling but via charge exchange that

is transported by diffusion of ions. This transportation process moves along the neuron's cell, down the axon and then through synaptic junctions at the end of the axon via a very narrow synaptic space to the dendrites and/or soma of the next neuron at an average rate of 3m/sec.¹¹

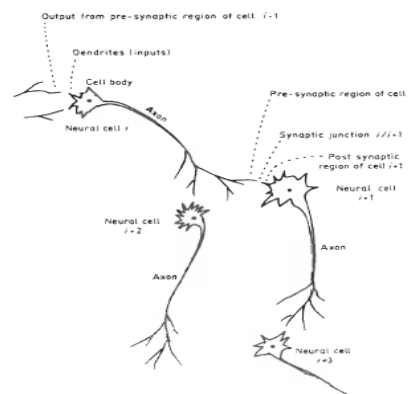


Figure 3.1 Illustration of Biological Neuron

Source: Daniel Graupe, *PRINCIPLES OF ARTIFICIAL NEURAL NETWORKS*, 2nd edition, University of Illinois, Chicago, USA

The basic principles of artificial neural networks were first created by McCulloch and Pitts in 1943, who tried to understand and learn how it processes the information. It contains 5 assumptions, setting a framework of ANNs. Later the Hebbian learning law due to Donald Hebb(1949) was also a widely applied principle. And it can be explained as that by repeating and persisting one action, some growth process or metabolic change will happen in one or both of these cells such that the efficiency of the cell will increase. In other words, the weight of one contributing neuron will increase if it approaches the final target. Then due to doubts about the capabilities of the early models, the research on ANNs declined after the 1960s.

But since the 1980s, the ANNs returned to people's view, resulting from several reasons: 1.the early simple model had been replaced by introducing the more complicated models with newest technology. 2. Powerful computers greatly improved the performance of the simulation of the complicated ANNs. 3. Introduction of multiple-layer ANNs enhanced and enlarged the area of appliance, including speech recognition, and pattern recognition. And now, more and more ANNs combine with other different algorithms or advanced technologies¹².

¹¹ Graupe, Daniel (2007). Principle of Artificial Neural networks, 2nd edition.

¹² Graupe, Daniel (2007). Principles of Artificial Neural Networks (2nd Edition)

3.1.2 Definition and terminology

"An artificial neural network is an information-processing system that has certain performance characteristics in common with biological neural networks. Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology"¹³

Table 3.1 Neural Network Glossary

activation / initialization function	Time-varying value that is the output of a neuron.
bias	The net input (or bias) is proportional to the amount that incoming neural activations must exceed in order for a neuron to fire.
connectivity	The amount of interaction in a system, the structure of the weights in a neural network, or the relative number of edges in a graph.
epoch	One complete presentation of the training set to the network during training.
input layer	Neurons whose inputs are fed from the outside world.
learning algorithms (supervised, unsupervised)	An adaptation process whereby synapses, weights of neural networks, classifier strengths, or some other set of adjustable parameters is automatically modified so that some objective is more readily achieved. The back-propagation and bucket brigade algorithms are two types of learning procedures.
Learning rule	The algorithm used for modifying the connection strengths, or weights, in response to training patterns while training is being carried out.
layer	A group of neurons that have a specific function and are processed as a whole. The most common example is in a feed-forward network that has an input layer, an output layer and one or more hidden layers.
neuron	A simple computational unit that performs a weighted sum on incoming signals, adds a threshold or bias term to this value to yield a net input, and maps this last

¹³ Laurene V. Fausett (1994), Fundamentals of Neural Networks: Architectures, Algorithms, and Applications

	value through an activation function to compute its own activation. Some neurons, such as those found in feedback or Hopfield networks, will retain a portion of their previous activation.
output neuron	A neuron within a neural network whose outputs are the result of the network.
threshold	A quantity added to (or subtracted from) the weighted sum of inputs into a neuron, which forms the neuron's net input. Intuitively, the net input (or bias) is proportional to the amount that the incoming neural activations must exceed in order for a neuron to fire.
training set	A neural network is trained using a training set. A training set comprises information about the problem to be solved as input stimuli. In some computing systems the training set is called the "facts" file.
weight	In a neural network, the strength of a synapse (or connection) between two neurons. Weights may be positive (excitatory) or negative (inhibitory). The thresholds of a neuron are also considered weights, since they undergo adaptation by a learning algorithm.

Source: *Earth online*, <http://envisat.esa.int/handbooks/meris/CNTR4-2-5.htm>

3.1.3 The neural structure and activation function

- The structure of a Neuron

Due to imitation of human neural network, each process in the neuron will contain receiving the input, transforming the data, and output.

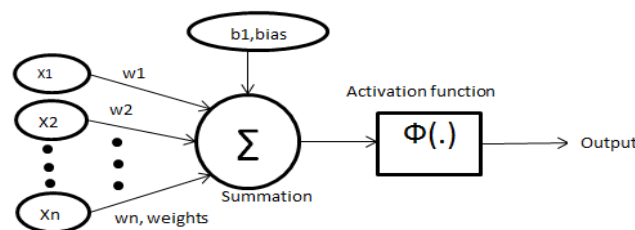


Figure 3.2 Constitution of a neuron

The input function of the neuron

$$y = \left(\sum w_{ji} * x_j + b \right)$$

Where w_{ji} is the weight of each connection,

x_j is the input,

b is the threshold.

- Activation function

The activation function of a node defines the output of that node given an input or set of inputs. Normally, these functions can take many forms, but they are usually found as one of three functions:

- Gaussian: $\phi(v_i) = \exp\left(-\frac{\|v_i - c_i\|^2}{2\sigma^2}\right)$
- Multiquadratics: $\phi(v_i) = \sqrt{\|v_i - c_i\|^2 + a^2}$
- Inverse multiquadratics: $\phi(v_i) = (\|v_i - c_i\|^2 + a^2)^{-1/2}$

Besides, in RBF (radial basis functions) network, they use the special activation functions which have extreme efficiency as universal function approximators.

3.1.4 Memorization and generalization ability and learning rules

For a successful model, the ability of memorizing and generalizing is very important.

- Memorization

Memorization means “to learn what happened in the past”. In practice, it consists of identifying, memorizing, and simply classifying the data into the “slot”

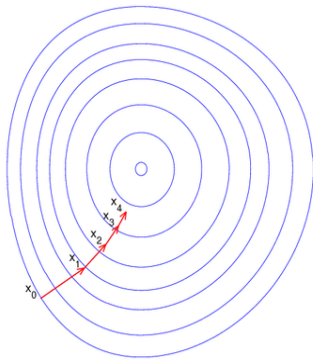
- Generalization

Generalization means “forecast the unknown data in terms of the principle studied from the known data”. In the ANNs, people usually adopt testing the model to check the generalization because there is no uniform standard to measure it. To some degree, we can compare the ANNs to the black-box model, which people only can check the output to verify the generalization instead of analyzing the structure inside.

- Learning

Learning contains supervised and unsupervised learning. In our case, the learning is supervised, which means both the information of the input and the reaction of the system are given. In other words, it is like teacher who knows all the answers teaching the students. In ANNs, the supervised learning is a process of memorizing data pairs. Both the input data and desired target are known. Although the target has been

provided, the time to terminate the learning process is hard to decide. The main reason



is that when the overall error is satisfied, the actual performance may be under-trained/over-fitted. If the model is trained too many times, the model will remember everything in the input data, including the error. But if the model is trained too few times, the model cannot identify the whole input pattern. In both situations, the performance of generalization will be damaged.

Figure 3.3 Illustration of gradient descent

Source: *gradient descent*, Wikipedia, http://en.wikipedia.org/wiki/Gradient_descent

Most learning rules are applied by changing the weight, which will decrease the error between the output and desired target. The typical method is Gradient descend.

$$\mathbf{x}_{n+1} = \mathbf{x}_n - \gamma_n \nabla F(\mathbf{x}_n), \quad n \geq 0.$$

The step gradient descent will repeat until the goal is achieved or stop condition is met.

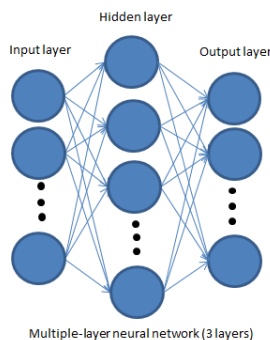
3.1.5 Single layer and multiple-layer neural network

- The single-layer network

A single layer network contains several neurons each having several inputs. This kind of network is commonly used for simple questions. But when it comes to complicated problems, the multiple-layer neural network will be more useful and practical.

- The multiple-layer network

The multiple-layer introduces the hidden layer/layers, whose neurons provide the



additional transforming. The hidden layer can be 1 layer or multiple layers. The higher the number of hidden layers, the easier the input can be. In other words, if the input data is insufficient, the complicated/multiple-layer network will be suitable by increasing the number of neurons and hidden layers.

Figure 3.4 Illustration of Multiple-layer neural network

3.1.6 The Back-propagation Network

Before introducing the RBF (radial basis functions) network, it is necessary to provide a brief introduction to the BP network, which is the most commonly used network and which will be adopted in Chapter 3.

1. Initiate the weight and bias by assigning random values between (-1, 1)

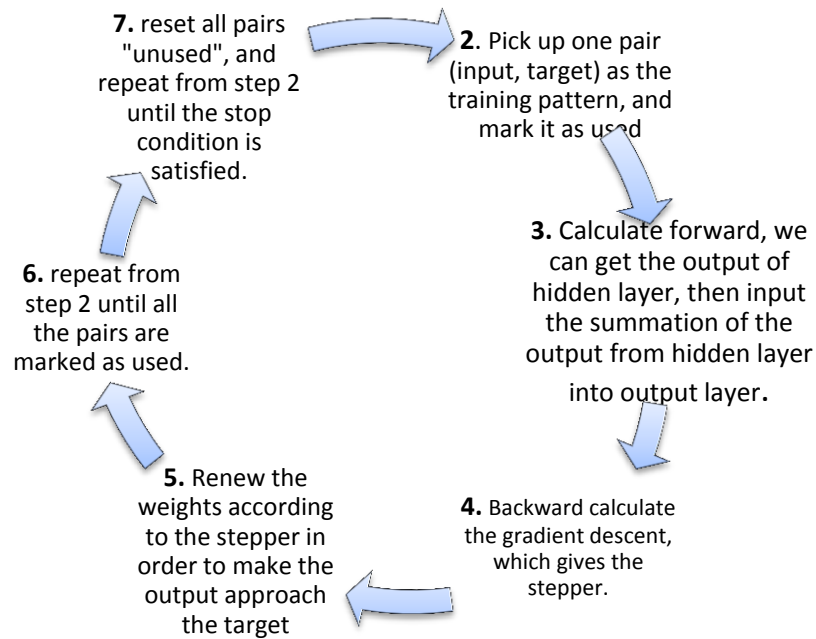


Figure 3.5 The procedure of BP network training

Source: Graupe Daniel (2007). *PRINCIPLES OF ARTIFICIAL NEURAL NETWORKS (2nd Edition)*.

The stop condition is usually defined as:

The error \leq goal of error set before or time of epoch reached

The initial selection of weight will determine the beginning place for the error. Too large a value will cause the error changing nearly to 0, and too small value will also make the value approaching too slowly.

3.1.7 The Radial basis function(RBF) network

● The introduction of RBF network

A radial basis function network uses radial basis functions as activation functions. It is a linear combination of radial basis functions, which have three layers: an input layer,

a hidden layer with a non-linear RBF activation function and a linear output layer. Or we call it as: forward, radial basis function as the activation function in the hidden layer, neural network.

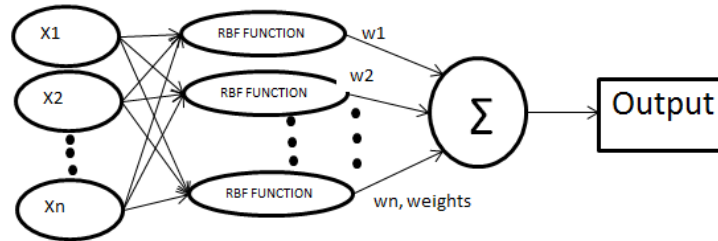


Figure 3.6 Illustration of Radial basis function neural network

The output can be expressed by:

$$y_k(x) = \sum_{j=1}^J w_{kj} \phi_j(x - c_j)$$

Where $j=1, 2, 3, \dots, J$

J is the number of neurons in the hidden layer

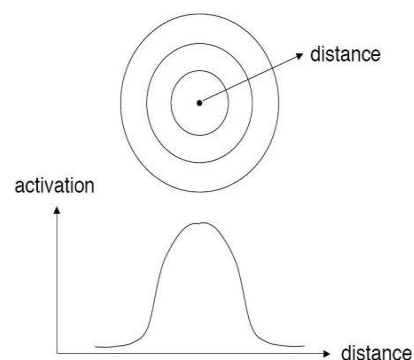
w_{jk} is the weight between the j neuron in the hidden layer and the k neuron in the output layer

c_j is the j center vector

x is the input vector

$$\text{And } \phi_j(x - c_j) = \exp \left[-\frac{(x - c_j)^T (x - c_j)}{2\sigma_j^2} \right]$$

Where: σ_j is the parameter of the width of the function, and T is transposition. This function is Gaussian Kernel function, most commonly used in RBF. And it means changing one parameter of one neuron will have little effect on the input, which is far away from the center of that neuron. In other words, the further away from the center, the smaller the effect it will make, which shows that only special



inputs can affect the RBF

. Figure 3.7 Illustration of Radial Basis Function

Source: *RBF neural network*, decision trees, <http://www.dtreg.com/rbf.htm>

● The procedure of RBF network

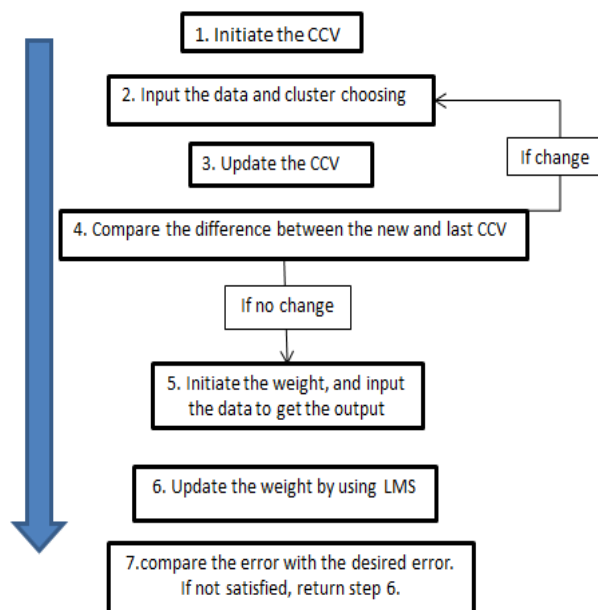
The general idea of RBF network is similar to BP network, which tries to adjust the weight to approach the stop condition by using Least Mean Square (LMS).

The difference is that in RBF, we need to decide the position of the center vector.

Normally we adopt K-means clustering method. It will update the central clustering vector (CCV) after input of data. Then we compare the current one with the last one, if the center clustering vector did not change, we can continue to calculate the weight by LMS, if the center clustering vector changes, then we repeat input of the data and compare them again until we find the unchanged center vector.

After adjusting the weight, the error meets the stop condition, the whole system terminates.

RBF network as a forward neural network, can approximate any kind of function, and can locate the universal optimal point, which avoids the local minimum in the BP network. Besides, researchers have proved that RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision.



The procedure of RBF network training

The best advantage of RBF network is the high efficiency of training and good generalization. It does not need too much input/output. When training the network, the RBF can automatically decide the number of neurons by comparing the performance instead of it being nominated by people, which saves a lot of time and energy.

Figure 3.8 The procedure of RBF neural network training

Source: modified from *RBF Neural Networks*, <http://www.dtrek.com/rbf.htm>, And *Radial basis function network*, http://en.wikipedia.org/wiki/Radial_basis_function_network

3.2 Data envelopment analysis(DEA)

In fierce competition, it is very important to measure how resources are used, whether they are optimally distributed. The more efficiently the resource is utilized, the higher profit the company can achieve.

Data envelopment analysis (DEA) is a non-parametric method in operations research and economics for the estimation of production frontiers. It is used to empirically measure productive efficiency of decision making units (or DMUs). In 1978, Charnes, Cooper & Rhodes (CCR for short) applied the linear programming to estimate an empirical production technology frontier for the first time. Since then, people have used DEA to solve various problems. There are two basic types of DEA: CCR-DEA, BCC-DEA.

- The CCR-DEA is the first DEA model obtained by Charine in 1978, and it is mainly used in the analysis of **technical efficiency**. It assumes constant returns to scale so that all observed production combinations could be scaled up or down proportionally.
- The BCC-DEA is raised by Banker, Charnes and Cooper in 1984, and this model is applicable for estimation of pure technical efficiency and **scale efficiency**. It allows for variable returns to scale and is represented by a piecewise linear convex frontier.

If we put the frontier of BCC and CCR into one graph, the efficiency point of CCR-DEA is the “absolute efficiency”. But the frontier of BCC-DEA can be generally divided into 3 parts, including “BCC-DEA efficiency>CCR-DEA efficiency” (means scale efficiency increase at the beginning stage), “BCC-DEA efficiency=CCR-DEA efficiency” and “BCC-DEA efficiency<CCR-DEA efficiency” (means scale efficiency decrease). So we can say that BCC-efficiency sometimes does not mean no room to improve. Figure 3.9 shows VRS change the frontier, compared with the constant CRS

frontier.¹⁴

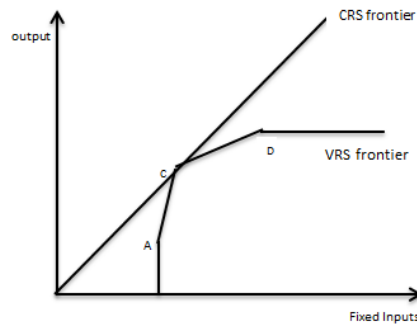


Figure 3.9 Comparison between CRS and VRS efficiency

Non-parametric methods have the advantage of not needing to assume a specific shape for the frontier, also not giving a specific equation relating to the output and input. For example, the typical parametric method, regression analysis, will need the underlying assumption and when estimating the efficiency, the estimation may be lower than the possible frontier. Besides, the regression model lacks the ability of multiple-target. But DEA still has a basic assumption: during the given period, all DMUs have the same technology. And the technology is a set of combination of input and output.

There is a simple example to explain DEA.

If we have N inputs, define them as $X_1, X_2, X_3, \dots, X_N$.

M outputs: $Y_1, Y_2, Y_3, \dots, Y_M$.

We can define $S = \{(X, Y) \mid Y \text{ related to } X\}$. And we have K observed DMUs under the same technology. So the data is $\{(X_K, Y_K)\} (K=1, 2, \dots, K)$. The DEA contains all the combination of these data by using a piecewise linear contour, and the contour's name is frontier. Then we get all the combination S.

$$S \approx \{(X, Y) \mid \sum_{K=1}^K Z_K X_K \leq X, Y \leq \sum_{K=1}^K Z_K Y_K, Z_K \geq 0 (K = 1 \dots K)\}$$

And if we add " $\sum_{k=1}^k Z_k = 1$ ", the set S will become "VRS"(variable return to scale), not the "CRS"(constant return to scale).

We can say that if any group of "input, output" fall into the range of S, that group data will be labeled as comparatively inefficient. In other words, these "inefficient data"

¹⁴ More information can be found Cooper, William W. Seiford, Lawrence M. Zhu, Joe. (2004). Handbook on Data Envelopment Analysis (pp 46)

show more input, and less output”. And if any data just stand on the “frontier” of the set S, we can say that data is technically efficient.

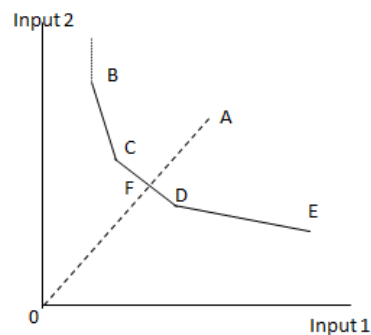


Figure 3.10 Illustration of measuring efficiency of point ‘A’

For example, if we have fixed the efficiency frontier “BCDE”, we want to calculate the relative efficiency of “A”. Connect “A” with the origin of coordinates, and measure the interval “FO”, and calculate the proportion of “FO”/”AO”. Then we get the relative efficiency of point “A”. The coordinates of point “F” give the desired input with the same output as “A”

3.3 Wavelet Transformation (Pre-processing data in BDI forecasting model)

3.3.1 Data transformation

Data transformation **converts** a set of data values from the data format of a source data system into the data format of a destination data system.

Data cleaning is the process of detecting and correcting (or **removing**) corrupt or inaccurate records from a record set, table, or database. Used mainly in databases, the term refers to identifying incomplete, incorrect, inaccurate, or irrelevant, parts of the data and then replacing, modifying, or deleting this dirty data.

As mentioned before, the source data, BDI is the representative of the dry bulk market. And in the shipping market, various cycles exist, including long-time trend cycles, seasonal cycles, and irregular cycles. But it is not easy to find a regular trend or even a rough shape, because too many unrelated factors affect the whole market. For example, in 2001, the shipping market was gradually recovering from the crisis in 1998, but the 9/11 attack disturbed U.S economics and swiftly spread to the whole

shipping market, then the BDI collapsed immediately to the bottom. An unexpected shock will hide the original trend, including cyclical factors.

So if we can eliminate the unexpected shocks in the data, and leave the data which contains the cyclical factors, the preprocessed data will be free of noise, which will improve the performance of the system by inputting cleaner data.

3.3.2 Fourier transformation

We can begin from Fourier transformation, which is the foundation of wavelet transformation. Simply stated, Fourier transformation is using a basis or combination of bases to express other functions, where the basis is a series of linear independent vectors, and other vectors can be expressed by this basis or combination of the bases. In other words, this vector is the common part of all the vectors, and we can use this common part to reconstruct the target vector. But in fact, there are many different bases, and selection of basis will decide the degree of complication in the calculation of the transformation. The selection of basis will depend on the goal of this transformation. **We want to select a basis which is the simplest but can retain the most signal characteristics.**

The formula is expressed as follows. Fourier thinks that all the functions can be expressed by a combination of function basis. And we use function sines and cosines to express $f(x)$.

$$f(x) = a_0 + a_1 \cos x + a_2 \sin x + a_3 \cos 2x + a_4 \sin 2x \dots \text{ where, } 1, \cos x, \sin x,$$

$\cos 2x \dots$ are the Fourier series. And this is an endless loop. Do not forget these functions should be oscillating functions. Where

$$\langle v, w \rangle = v^T w = \sum_{k=1}^n v_k w_k = 0$$

These pictures are simple examples of Fourier transformation.

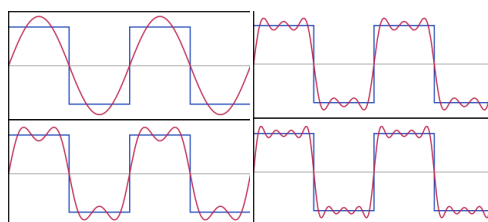


Figure 3.11 Example of Fourier Transformation

Source: Wikipedia, Fourier transformation. http://en.wikipedia.org/wiki/Fourier_transform

But Fourier transformation has some disadvantages: 1. Frequency domain and time domain cannot both exist. In other words, the Fourier transformation will lose the time domain. People cannot speculate what exactly the time is, according to the result of the transformation. 2. Fourier transformation is suitable in the linear and stable data, but when it comes to non-linear and non-stable data, the performance of transformation will be compromised.

3.3.3 Wavelet transformation

Wavelet transformation can be called “wavelet analysis”, but actually, Fourier transformation is also a wave analysis. The difference between the two transformations is the waves, which are sines/cosines with infinite energy in Fourier transformation and a relatively short and finite energy wave in wavelet transformation. No matter if you amplify or scale the sines/cosines, the basis in Fourier transformation is only sines (the cosines can be converted into sines by shifting). But in wavelet, the basis is not fixed, which means you can modify it as long as the modification is subject to the characteristic and nature of wavelet.

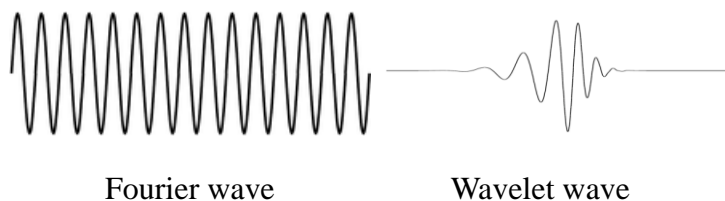


Figure 3.12 Illustration of Fourier wave and wavelet wave

The core idea of wavelet is similar to Fourier transformation, by select the appropriate basis, to decompose the function. Every wavelet contains mother wavelet and scaling function (father wavelet). So any kind of function basis can be a set of shifted and scaled mother wavelet and father wavelet, and the range of shift is related to the degree of scaling.

There are many kinds of wavelet systems, including different mother wavelet. And this is the approximate form of wavelet expansions.

$$f(t) = \sum_k \sum_j a_{j,k} \psi_{j,k}(t)$$

Where the wavelet series is $\psi_{j,k}(t)$, and the combination of these series form the orthonormal basis

Definition: if $\psi(t) \in L^2(\mathbb{R})$ satisfy the condition

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\Psi(\omega)|}{|\omega|} d\omega < \infty$$

Then $\psi(t)$ becomes admissible wavelet (or mother wavelet), and $\Psi(t)$ is the transformation of $\psi(t)$

The wavelet function consists of the mother wavelet, can be expressed:

$$\psi_{a,\tau} = |a|^{-\frac{1}{2}} \psi\left(\frac{t-\tau}{a}\right)$$

The definition of the continuous wavelet transformation: if $f(t) \in L^2(\mathbb{R})$, then by applying mother wavelet $\psi_{a,\tau}(t)$, the transformation of $f(t)$ is

$$(W_\psi f)(a, \tau) = \int_{-\infty}^{+\infty} f(t) \psi_{a,\tau}(t) dt$$

Reconstruct function:

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \frac{da}{a^2} \int_{-\infty}^{+\infty} (W_\psi f)(a, \tau) \psi_{a,\tau}(t) dt$$

Discrete wavelet transform can be expressed

$$\psi_{j,k}(t) = a_0^{-\frac{j}{2}} \psi(a_0^{-j} t - k\tau_0), j, k \in \mathbb{Z}$$

Reconstruction function:

$$f(t) = c \sum_{-\infty}^{+\infty} \sum_{-\infty}^{+\infty} W_{j,k} \psi_{j,k}(t)$$

where c is a constant value.

Because the time window and frequency window is related, by applying a different

value of a , the scale of time window and frequency window can be adjusted. When the $|a|$ increases, the frequency window becomes smaller with the time window becoming bigger. For example, when we analyze the BDI data, the small time window together with big frequency window will be suitable for the high frequency part. Vice versa, when it comes to the low frequency part, the big time window and small frequency window can be applied. Due to the flexible structure of wavelet function, the performance of analysis of BDI will be improved.

CHAPTER 4

CASE STUDY 1: FORECASTING BALTIC DRY INDEX

4.1 Introduction of Baltic Dry Index (BDI)

4.1.1 The freight rate index

BDI, as a maritime index, is also a kind of freight rate index.

The freight rate index is the ratio between the current freight rate and the reference period freight rate, reflecting the movement of the freight market. In other words, the freight rate index gives the ship owners and shipper a general description of the market, and the development trend. So far, the published freight index can be divided into 2 parts: tramp shipping freight index, and liner shipping freight rate. And the tramp freight rate index is further composed of voyage charter freight index and time charter freight rate. The liner shipping freight rate includes the container freight rate index. Now there are several influential freight rate indexes published: Baltic dry index, Clarkson indices, Lloyd`s shipping economist tramp trip charter indices, Maritime research freight indices, German sea freight indices, Hamburg index for containership time-charter rates, and HARPEX.

As mentioned, the freight rate index gives a general description of the market, and the shipping market is very specialized, so it needs an integrated index to summarize what is happening in the market. In the current shipping market, many factors affect the freight, including weather, political factors, economic and factors. The index, performing as the traffic lights, shows the basic material for companies to research and forecast in order to reduce risk. For the charterer, they will decide on a certain kind of ship chartering in the future based on the index research so as to maximize their profit and have a better preparation. For ship owners, the index reveals the trend

of the market, helping ship owners plan their investments, like building/demolishing or buying/selling ships, and finally keeps ship owners in an advantageous position for the future. In addition, the index is also commonly used for the future market, measuring the risk and improving the effectiveness of business planning by trading on the future market. The purpose is to hedge the risk in the highly fluctuating shipping market.

4.1.2 Baltic Dry Index

In 1985, a system was created in the Baltic exchange, establishing a daily freight index. It is called Baltic Freight index (BFI) which shows the daily weighted average freight rate level and daily weighted average trip time charter hire level of the dry bulk cargo shipping market. The BFI is a combination of dry cargo voyage and time charters, each of which is weighed within the index decided by the importance in the market. Each route has been carefully defined within narrow parameters and given an individual “weight” so that the modified importance will be graded in the combination. Each route data is from market information provided by a group of ship brokers who are appointed by the Baltic Exchange. The date of 4th, January, 1985 was set at 1000 index, composed of freight rates in 13 routes, covering coal, iron ore, grain, phosphate rock, bauxite, excluding time charter freight. As time changes, the routes and weight also vary from time to time in order to represent the entire dry market. Now the index has been reduced to 11 routes and four of them are spot time charter routes. In 1999, the Baltic Exchange decomposed the Baltic freight for Panamax and Capesize into Baltic Panamax index (BPI), and Baltic Capesize Index (BCI), so BCI, BPI, and BHMI replaced the Baltic Freight index (BFI), introducing a new index, the Baltic Dry index (BDI). BDI is calculated by a combination of 1/3 of BCI, 1/3 of BPI, and 1/3 of BHMI.

Because BDI is composed of the freight in specific routes, the rise of BDI shows an average freight rate increase. And normally the rise in BDI is an indication of a stronger demand for commodities from countries or the insufficient capacity in several specific routes. When the shipments increase, economies tend to do well and

vice-versa. It can be seen that the BDI can be very volatile, at times simulating a roller coaster ride on the charts. **Actually BDI is a typical form of expression of dry bulk demand-supply model.**

As mentioned above, the high fluctuation of dry bulk market results from the reaction between both volatile demand and supply. In the following paragraphs, the contemporary situation will be analyzed, along with how demand-supply mechanism affects BDI, which makes BDI a signal of the market.

4.1.3 BDI, result of dry bulk Demand-Supply mechanism

● The demand of the dry bulk market

As mentioned above, the major 5 dry bulk cargoes are a necessity for the development of countries. The financial crisis frustrates many countries' economies, hitting merchandise industries heavily, and resulting in the recession and economic contraction. Recently the Chinese government released an economic growth rate expectation in the second quarter breaking below 8%, and many other countries claim 2012 will be a tough year. For the dry bulk market, it is definitely winter.

■ **Iron ore**, as the biggest dry bulk commodity, is heavily affected, causing the dry bulk shipping market hovering at low level. Although in 2010 the dry bulk market rebounded, later the weak economy drove the iron ore trade down again. So far, the signal of slowing-down economies keeps pushing down the demand.

■ For **coal**, the contradiction between demand and supply upgrades with new emerging capacity. Take China for example, in 2012, the GDP has slowed down, resulting in a decline of the consumption of energy, 70% of which is generated by coal. New forms of energy have begun to seize the share of coal, such as LNG, solar power, and wind energy. In addition, the slowing down of steel production also contributes to reduction of demand.

■ For **grain**, since 2011, under the pressure of the earthquake in Japan, European debt, American debt and adverse weather, the recovery of the global market has slowed down, causing the whole grain market to follow the trend from high to low. What is worse, new members have entered the grain market, causing the

expectation of continuous grain production to be corrected toward the optimistic direction. On the demand side, the industrial consumption of grain is driven down due to the weak merchandise production.

But we should also be aware that demand for dry bulk shipping is inelastic because dry bulk transport cannot be substituted by other modes because the economies of scale has been well demonstrated in dry bulk transport.

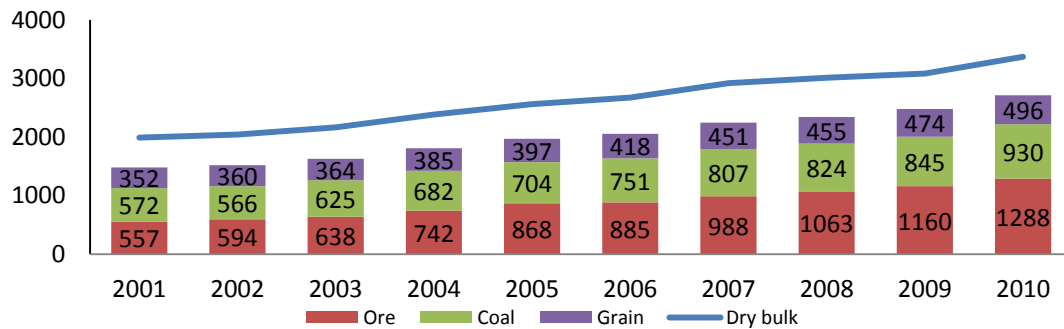
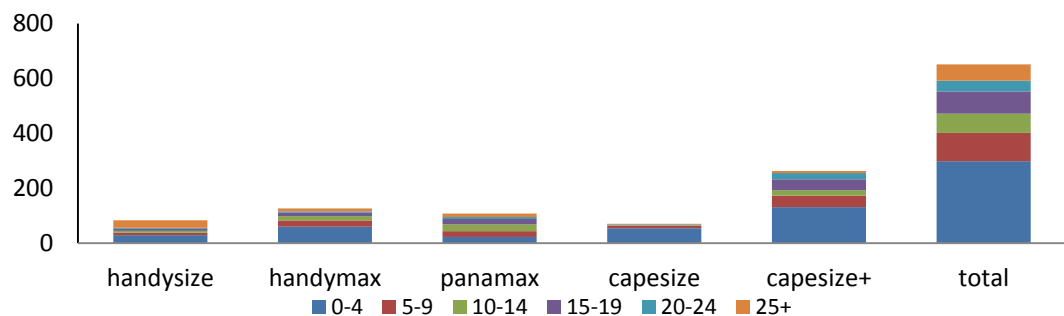


Figure 4.1 Dry bulk demand from 2001-2010

Source: Data collected from *Shipping Statistics yearbook 2011*, Institute of shipping economics and logistics

● The supply of the dry bulk market

The ship supply includes: new-building market, scrapping market, and laid-up/casualty tonnage. For the bulk carrier, the life cycle lasts around 20 years¹⁵, depending on the structure, steel quality, maintenance, and trading pattern. Since 2002, ship owners began to increase investment in the dry bulk fleet in order to meet the growing demand, especially from China. Nowadays, the distribution of age clearly shows that 60% of the dry bulk fleet was built within 10 years.



¹⁵ The Average age of merchant ship is 27.8 years. From Dr Nikos E Mikelis. A statistical overview of ship recycling.

Figure 4.2 Dry Bulk fleet age Distribution, million dwt. July-2012

Source: data collected from <http://www.lloydslist.com/ll/marketdata/dryCargo/dryBulkSupplyPage.htm>

■ New building market.

First of all, the new-building market is decided by the shipping market, in other words, the passion of the ship owner and direction of demand from cargo owners will drive the new-building market in the form of order books. When the market is in an uptrend, the ship owner will invest in new ships according to the expectation of high freight. Even in the downtrend, a few speculators will also build new ships because of the relatively low price. From preparing the steel plate to final sea trial, ship building is a capital-intensive and time-consuming project. This long lead time will hide the new capacity in the future and when it pours out suddenly, the new ships will lead to a more severe imbalance due to blind herd mentality. Other than the traditional optimists and speculators, some strong cargo owners also begin to seize market share because of their strategy plans, for example, VALE. Vale as the global leading mining company, invested to build 35 VALEMAX vessels by 2013. Each ship has a dead weight of around 350K-400K. Although by economies of scales, the VALEMAX can easily achieve the environmentally-friendly goal and around 20% transport cost cutting per DWT. The flooding of tremendous capacity will heavily disturb the dry bulk market, causing the downturn in freight market to become even worse. People may wonder how VALE handled the huge loss in the freight market, and why. The answer is that: 1. Controlling the transport will improve the company`s competitiveness. 2. By pulling down the freight, Vale can achieve a smaller gap of iron ore price compared with that from Australia.

Table 4.1 Iron ore freight difference between Brazil-China and W-Australia

	2008 peak freight	2012 bottom freight
BRAZIL - CHINA, \$	106	20
W.AUSTRALIA – CHINA \$	48	8

Source: various sources

China, the world's biggest ship-building country, has claimed that the winter of the Chinese ship-building market has come. As mentioned before, the ship-building market is driven by the freight market and international trade. A financial crisis like a sharp needle pierces the bubble of shipbuilding, terminating the mindlessness. According to Clarkson research, from January to May, the new building order was 6.7 million CGT, a 50% reduction in order book tonnage based on data from last year. Many people think that in the next 3 to 4 years, 50% of the ship building yards in China will go into bankruptcy because of no orders and troublesome cash flow. Although many ship owners cancel, delay orders or sell the unfinished ship under the price, the fleet inevitably expanded significantly due to the huge base, from 415 million DWT in the end of 2008 to 630 million DWT in March of 2012. So far the future of ship building yards is not clear.

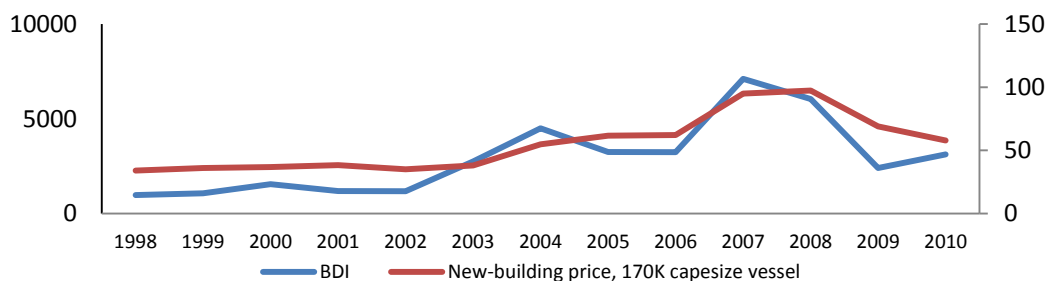


Figure 4.3 BDI Vs. New building price of Capesize Vessel

Source: Data collected from <http://ship.csi.com.cn/face/hyzzNews/20120702092706.html>

■ Scrapping market.

The scrapping market for the shipping industry, as the stomach of the shipping market, demolishes old vessels in order to cut down capacity, improve the structure of the fleet, and is the only way to dispose of the old ships when the ships are too old to be competent. Whether the scrapping market is prosperous or not depends on the shipping market. Generally speaking, when the market is

booming, short of supply, ship owners will not actively send their old vessels into demolition, but try to delay the demolition of the ship so as to continue providing service instead. When the market is depressed, overcapacity, the ship owner will accelerate the recycling of ships so as to reduce loss and upgrade their fleet. The broken-up tonnage is just the opposite of freight rate, revealing a negative correlation against BDI.

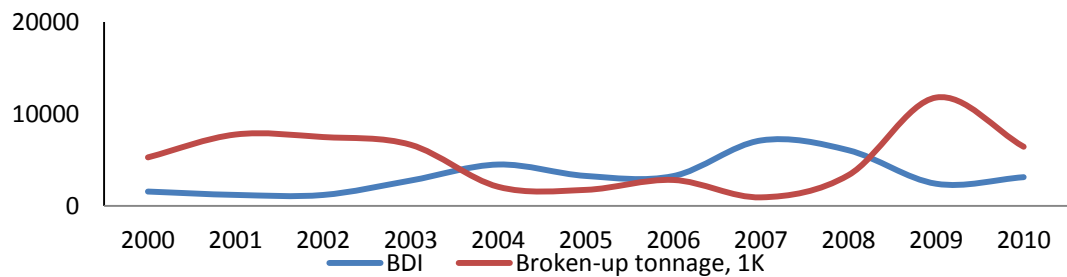


Figure 4.4 BDI Vs. Broken-up tonnage, 1K tonnage

Source: Data collected from *Shipping Statistics yearbook 2011*, Institute of shipping economics and logistics

So far, the demolition of old vessels is the common sense approach to reduce overcapacity and allow the market to digest the new capacity. According to a report from Braemar Seascope, 900 million DWT ships were scrapped in the first 3 months of 2012. Some people even say in the next 5 to 10 years, 30% of the fleet will be demolished. Besides, the traditional ship breaking countries, such as Bangladesh, India, Pakistan, China, and Turkey, are all developing countries, requiring huge amounts of steel to supplement the expansion of their infrastructure. The scrapping market is flourishing, and “green recycling” appeared with the Hong Kong Convention in 2009. Although this convention aims to address the safe and environmentally sound recycling of ships, the extra cost causes ship owners to turn their backs to it; for example, before scrapping, cleaning the hazardous material, and taking care of the safety of workers. This convention needs to meet 3 criteria before it comes into force¹⁶, but so far not

¹⁶ Further reading about HK convention can be found from <http://www.imo.org/ourwork/environment/shiprecycling/pages/Default.aspx>

one single country has ratified it. So the impact of HK convention is limited in the recycling of ships, and this market will continue flourishing.

■ The laid-up tonnage.

Laying-up ships makes good business sense during tough times. Not only does it allow ship owners and operators to avoid non-profitable journeys and over supply, it also reduces wear and tear, crew costs, fuel consumption and insurance premiums during the idle period.

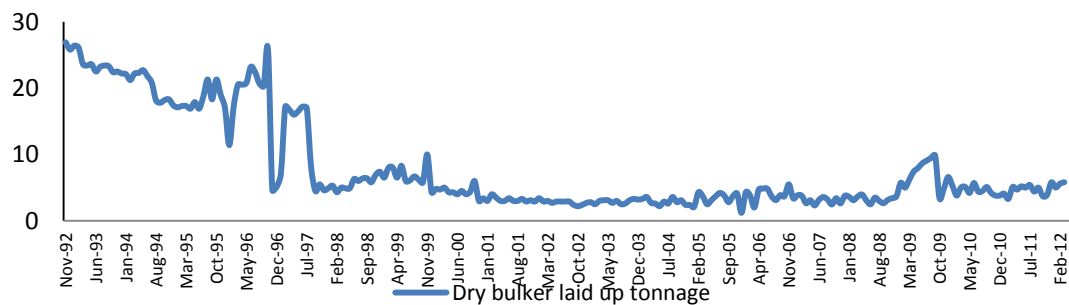


Figure 4.5 Dry Bulker Laying up Tonnage, Million Tonnage from 1992 to 2012

Source: Data collected from *Lloyd's List economist monthly*, from 1992 to 2012

But actually we did not see too much tonnage laid up after the financial crisis, compared with the 1998 crisis. The reason is that nowadays laying up vessels is different from that in the previous times. 20 years ago, shipowners laid up vessels like abandoning or deserting the ship, with even no crew on board. But now ship owners need to man the laid-up the ship to take care of the maintenance, preservation, security and safety issues according to the regulations, and they also require class maintenance¹⁷, insurance during lay-up and reactivation fees. After weighing the loss in the charter market and the cost from laying up the vessel, the ship owners prefer to choose to operate the ship, but in slow steam.

■ Second hand ship market.

It is not necessary to mention too much about second hand ships, although this market is rather active. Generally speaking, ship owners will sell their old ships

¹⁷ Class maintenance depends.

as second hand ships when this ship has broken-even in cost-efficiency. The buyer will purchase a SH ship at a reasonable price, depending on the depreciation, physical condition, and maintenance. And then usually the buyer will put this ship into a lows risk or revenue route to get the residual value. The advantage of SH ships is low price, easy handling (because it is an old ship, crew are familiar with her), and the disadvantage is high maintenance cost and potential risk.

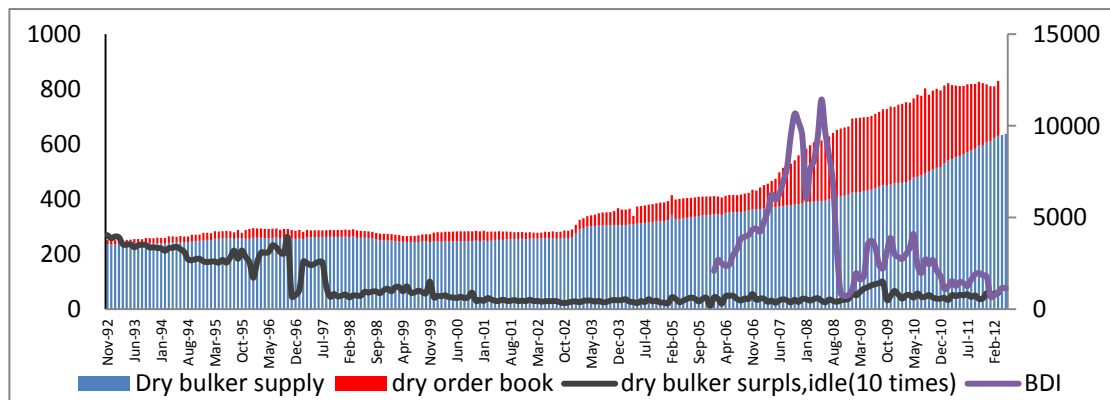


Figure 4.6 Dry Bulk Supply from 1992 to 2012

Source: Data collected from *Lloyd's List Economist monthly* from 1992 to 2012

- **The mechanism of Demand-Supply model**

We have assumed that the shipping market is very close to a competitive market, which will follow the laws of demand and supply. This Figure shows the relationship between demand and supply, and the final balance “freight” is also decided by the two sides. According to the laws of demand and supply, when the quantity of demand and supply vary, the balance, the freight will change to the next balance point. But for different production/service, the price elasticity of demand and supply varies. For shipping elasticity, it means whenever sea freight changes, what is the reaction of seaborne trade and/or ship supply? In other words, It is also about how efficiently the price message is received and how soon, consequently, a reaction occurs and an equilibrium is reached.

In short term, supply has a characteristic “J” shape, and in the short term, demand is inelastic. Freight cycle peaks and troughs are produced by the inelastic demand curve

moving along the supply curve. When it arrives at the “kink” of the supply curve, freight rates move above operating costs and become very volatile. Beyond this point economics can tell us little about the level of freight rate; it is entirely based on the auction between buyers and sellers for the available capacity.

In the long term, the volatile freight cycles ought to average out a `natural` freight rate which gives investors a fair return on capital. Although this is true in theory, some experts warn that we should not rely on it. In a constantly changing world, long-term average earnings are not subject to rules. In the past, the over-eagerness of shipping investors has tended to keep market return low, and enough shipping fortunes have been made to keep hopeful investors in the business.

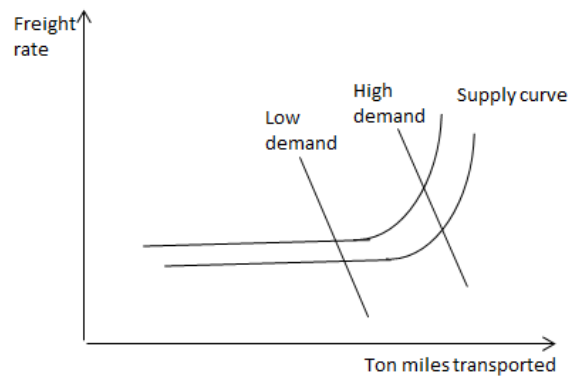


Figure 4.7 Demand-Supply mode

4.1.4 The BDI development

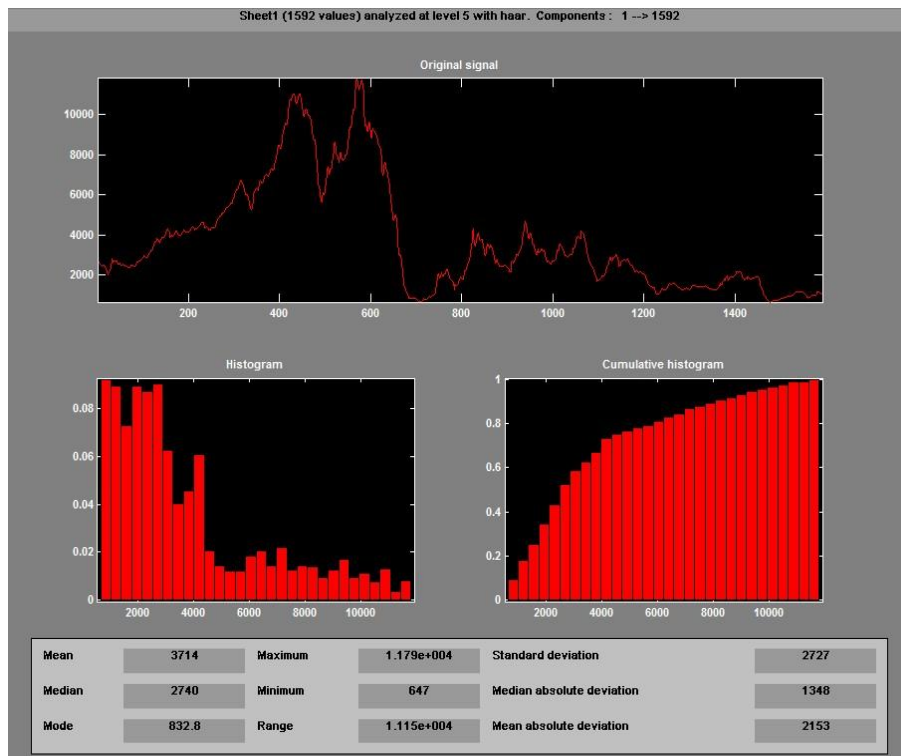


Figure 4.8 Statistic analysis of BDI (2005.12.07-2012.07.20) by MATLAB

The period of collected BDI is from 2005-12-07 to 2012-07-20. This Figure is the statistic result, showing the high fluctuation and the possibility of each interval. Most of BDI data fall into the area of 1000-3000, and the possibility of above 4000 or below 1000 becomes smaller and smaller. Normally, the break-even point for shipping companies is approximately 2000, which will float due to the fluctuation of bunker price and various costs. We can see from 2005 BDI is much higher than 2000, especially in 2007 and 2008 BDI reached a peak of “11146”. Then after the financial crisis BDI free fell from, to around “650” in 2009, and many shipping companies suffered severe losses. In 2010, BDI Miraculously rebounded and stayed for almost the whole year above “2000”. When people thought that shipping had overcome the tough time from 2008, looking forward to a full recovery, the following 2011, and the first half of 2012 extinguished their just ignited hopes. According to a report from Clarkson, January-June 2012, although now the crude oil prices have gone into the downstream, the margin of bunker prices cannot compensate for the loss in the freight. They forecast the dry bulk trade volume at a 4% per year increase rate, comparing with a 6% yearly increase rate in 2011. They also convert the dry bulk trade into ship capacity, and after comparing with the current capacity of the fleet, they found the ratio is 1:3.6, showing how serious overcapacity is.

People absolutely know that the market does not welcome any new dry bulk ships now, but in fact they cannot stop the new ship delivery because of the contracts with ship yards reached several years ago; otherwise, the half-finished ships will be in vain and ship yards will even claim more compensation against ship owners.

4.2 The goal of this case study and data collection

The goal of this case study was mentioned above in Chapter 1, forecasting the BDI, in order to help the shipping industry to withstand risks.

The data was collected from the website of Lloyd’s List Economists, from 2005-12-07 to 2012-07-20.

4.3 The application of wavelet neural network to BDI forecasting

In the previous paragraph, the cause of high fluctuation in BDI: Volatile balance between dry bulk demand and supply was analyzed. So applying ANN to forecast BDI will be a good choice, compared with the poor performance of the regression model in high fluctuating data prediction.

4.3.1 The whole process illustration

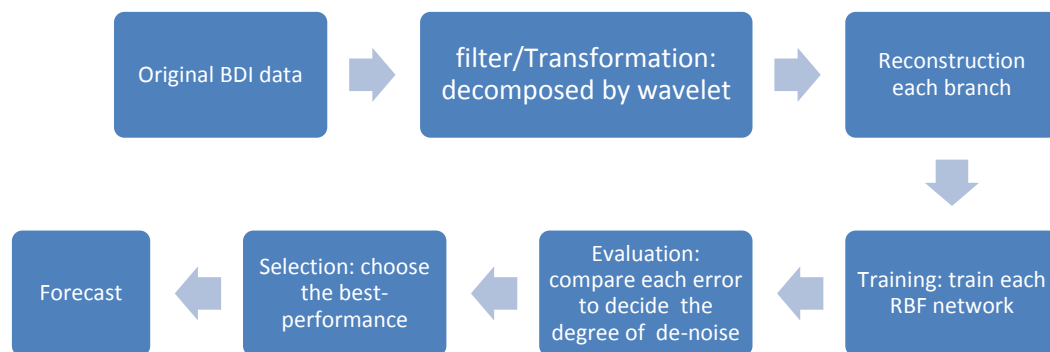


Figure 4.9 Illustration of the procedure of wavelet neural network

4.3.2 Transforming BDI data by wavelet

- **Choosing the wavelet by comparing each decomposition of BDI**

BDI, as the representative of the dry bulk market, is affected by various factors. In the development of BDI, various unexpected events may happen at any time, resulting in the increase/decrease of BDI in a short time, so, to some degree, **the “noise” will hide the true trend of BDI.** Researchers have confirmed the shipping market has the characteristic of periodicity, so by applying wavelet analysis, we can decompose the BDI into several different frequency-range signals as mentioned before. Besides, we do not need to strictly comply with the numbers of levels in decomposition. because in this case, BDI do not really follow the classical decomposition, which has the clear definition in each level. However, the low-frequency part is much smoother than the original signal, and this characteristic can be considered as the periodicity of the market, which follows the stable, smooth way. Other higher-frequency parts can be described as signs of different degrees of influence in the market.

It was mentioned that the irregular components may contain useful data, but when we introduce that part, the improvement of performance of the model depends on many factors, including selection of wavelet.

Now, the performance of each wavelet-decomposition in the low-frequency part is checked.

Haar 3 - wavelet

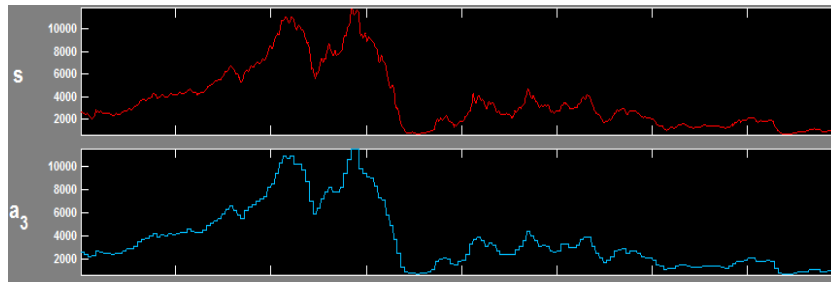


Figure 4.10 Haar 3 Low-frequency part of BDI reconstruction by MATLAB

Sym 5, 3 level - decomposition

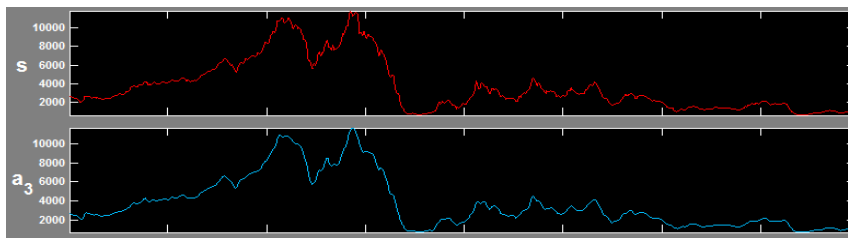


Figure 4.11 Sym5, 3 Low-frequency part of BDI reconstruction by MATLAB

Coif 3, 3 level - decomposition

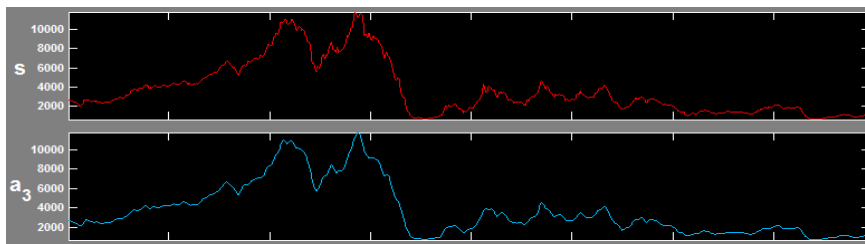


Figure 4.12 Coif3, 3 low-frequency part of BDI reconstruction by MATLAB

Bior 2.4, 3 level - decomposition

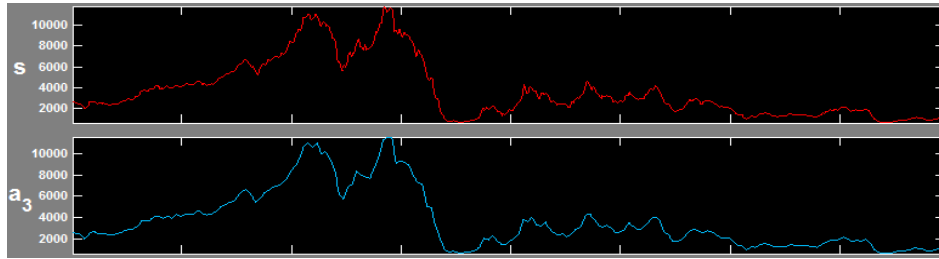


Figure 4.13 Bior2.4, 3 low-frequency part of BDI reconstruction by MATLAB

db 5, 3 level – decomposition

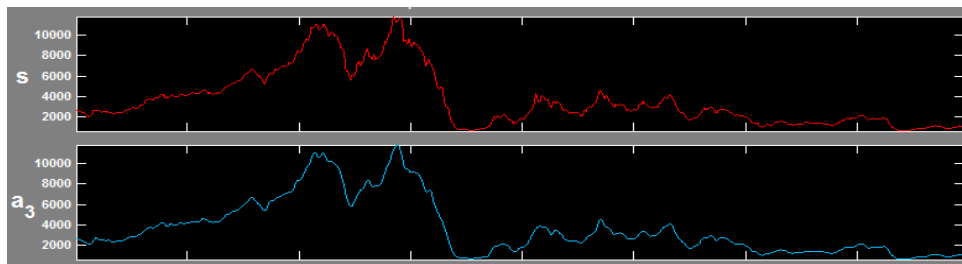


Figure 4.14 db5, 3 low-frequency part of BDI reconstruction by MATLAB

Among these low-frequency parts of the BDI, the db decomposition keeps most of the characters, followed by sym wavelet decomposition. Of course, other wavelets also provide good re-expression ability.¹⁸

- **The application of db3,5 wavelet to BDI**

- Decomposition

The db3 (5 level) wavelet is adopted to decompose the BDI data, and the wavelet tree shows the structure of decomposition.

$$\mathbf{BDI}=\mathbf{a5}+\mathbf{d1}+\mathbf{d2}+\mathbf{d3}+\mathbf{d4}+\mathbf{d5}$$

It is also known that $\mathbf{a4}=\mathbf{a5}+\mathbf{d5}$, $\mathbf{a3}=\mathbf{a4}+\mathbf{d4}$, $\mathbf{a2}=\mathbf{a3}+\mathbf{d3}$, $\mathbf{a1}=\mathbf{a2}+\mathbf{d2}$, $\mathbf{BDI}=\mathbf{a1}+\mathbf{d1}$.

In other words, the d_x can be considered as the high-frequency part stripped from a_{x-1} .

All $a5$, $d5$, $d4$, $d3$, $d2$, $d1$ will be the data to be input into each RBF neural network.

¹⁸ The details of each wavelet can be found in APPENDEX

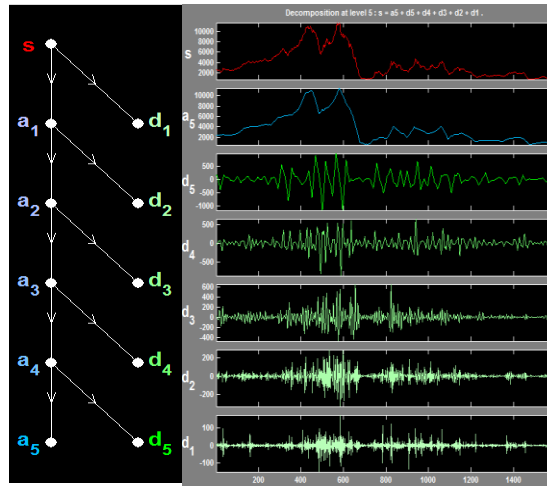


Figure 4.15 Illustration of decomposition of BDI by db3, 5 wavelet

■ Reconstruction

Because $BDI = a_5 + d_5 + d_4 + d_3 + d_2 + d_1$, $a_4 = a_5 + d_5$, and so on, all different degrees of de-noise data: a_5, a_4, a_3, a_2, a_1 , BDI' can be reconstructed¹⁹.

a_5 can be considered as the highest degree of de-noise data, most high-frequency parts removed. And a_4 is 2nd degree of de-noise data, d_5 part removed. The aim of reconstruction is to measure each deviation between the de-noise data and original data, evaluating the overall deviation.

4.3.3 The application of RBF network

● **Input pattern and RBF network setting**

■ Input pattern

Due to the supervised-learning network, each group of input should match a “teacher” output. BDI are published by Baltic exchange in the working days, which occupy 5 days in one week, so we can consider BDI as the time-series data.

Although we decompose BDI into $a_5, d_5, d_4, d_3, d_2, d_1$, all components are still time-series data. Because normally one month will contain approximately 22 working days, we choose every consecutive 22 data as one group of input and the next one data as the target. Shift the lag window one by one to build the whole input and target/output in each component until the lag reaches the last one.

Input/output pattern:

¹⁹ BDI' means the reconstructed BDI, summation of $a_5, d_5, d_4, d_3, d_2, d_1$, but almost same as original BDI.

```

(***** ) (#) #####...
*(*****#) (#) #####...
**(*****##) (#)#####...
.....

```

This is repeated until the lag reaches the last one as the target

So it forms 1548 groups of input/output in each component for training, and the last 22 groups of input/output are kept for testing.

■ Normalization

After fixing the input/output pattern, the data still need to be normalized in order to improve the efficiency of the calculation. And MATLAB provides the function “premnmx” to make the data fall into the interval [-1, 1].

$$t' = \frac{2(t - t_{min})}{t_{max} - t_{min}} - 1$$

Where t' is the data after normalized

t_{min} is the minimum value of the data

t_{max} is the maximum value of the data

t is the current data to normalize

■ RBF Network setting

Due to different degree of de-noise, the fluctuation of each part will be different, so different training goals are adopted²⁰ for each network. Inappropriate goals will significantly extend the training time, causing over/insufficient training. Besides, in this case, we find that when spread rate=1.5, the network gives the best fitting performance. Too large a spread value will cause extremely high fluctuation, but too small a spread will make the curve too smooth.

● Training and testing in each branch and evaluation

In each branch, 1548 groups of normalized data are input into RBF network, and the last 22 groups are used for testing.

With the accumulation of forecasting, the forecasting error will increase²¹, but the

²⁰ Goal of low-frequency part(a5) is smaller due to less fluctuation, and high-frequency parts(d1, d2, d3, d4, d5) will have bigger goal

²¹ For example: a4=a5+d5, which a5 and d5 are both forecasted. And a3=a4+d4, etc.

reconstructed curve will approach the original BDI curve.

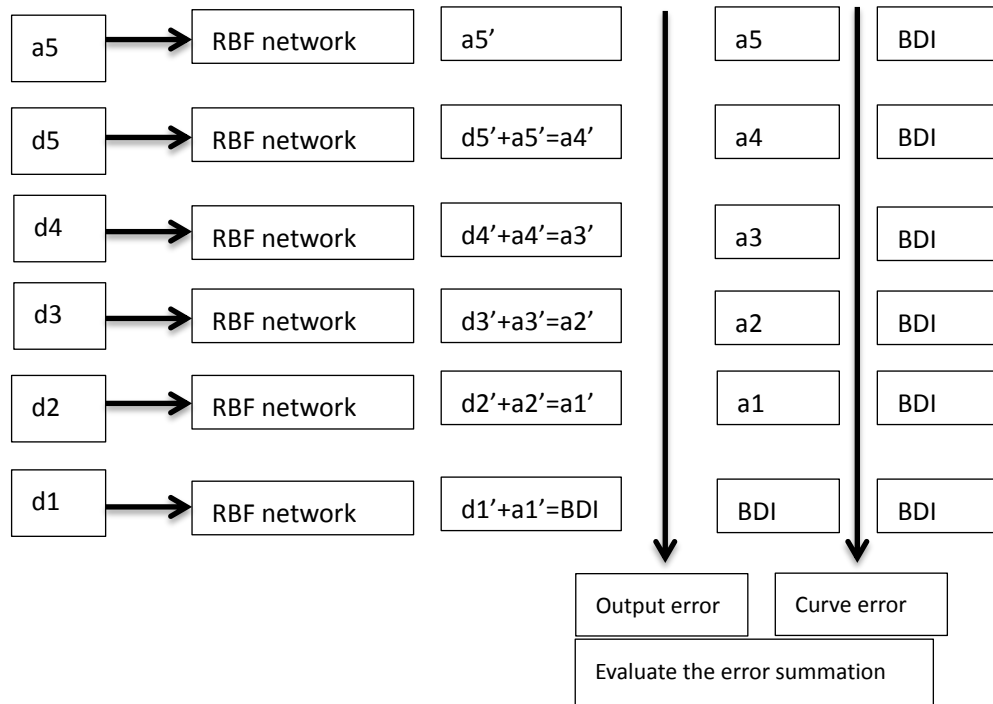


Figure 4.16 The process of training, testing, and evaluation

■ a_5

The blue curve is a_5 , filtered curve, highest degree of de-noise/cleaning. The orange curve is the original BDI curve.

a_5 (22-1 pattern) is input into RBF network and train it, and then input the a_5 test data to the trained network to get the output a_5' . Then compare the difference between a_5 and a_5' by MSE.

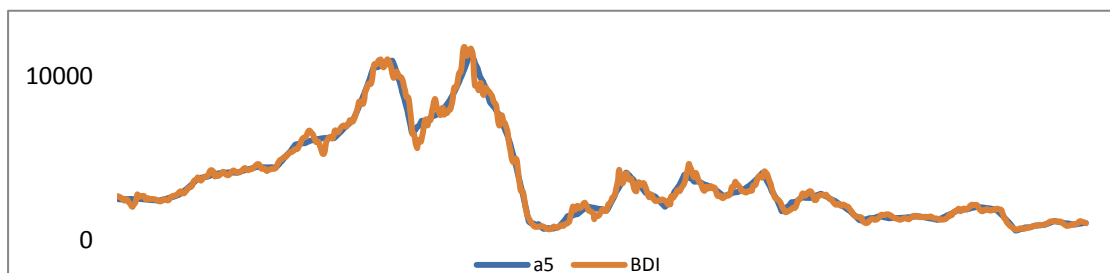


Figure 4.17 Comparison between reconstructed a_5 curve and BDI

Training goal: 0.005 (100 epochs), spread rate: 1.5

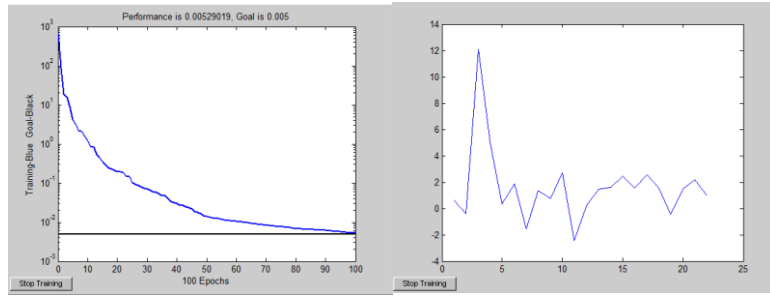


Figure 4.18 Training curve and Error curve of a5 RBF network

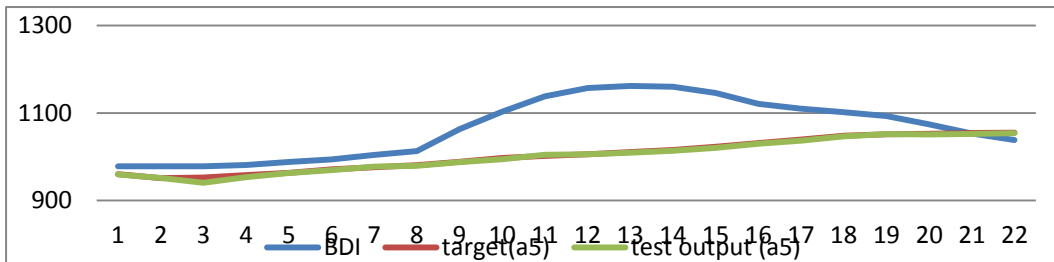


Figure 4.19 Comparison among network output a5, target, and original BDI

■ a4

Because $a4 = a5 + d5$, and $a5'$ has been forecasted in the previous step, $d5'$ is needed. Employ the same 22-1 pattern to train and test the trained network by input $d5$ test data.

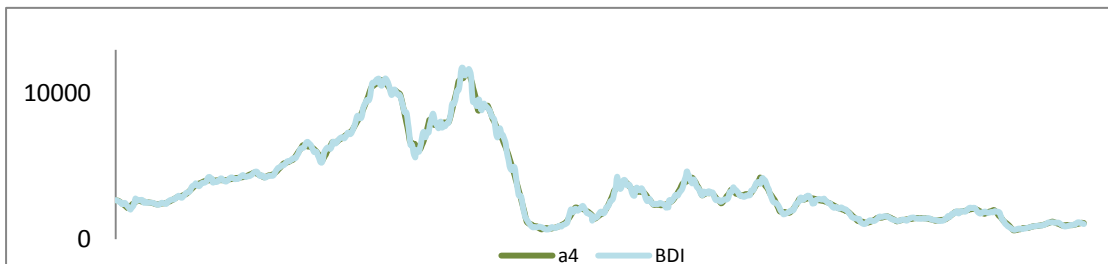


Figure 4.20 Comparison between reconstructed a4 curve and BDI

Training goal: 0.015 (400 epochs), spread rate: 1.5

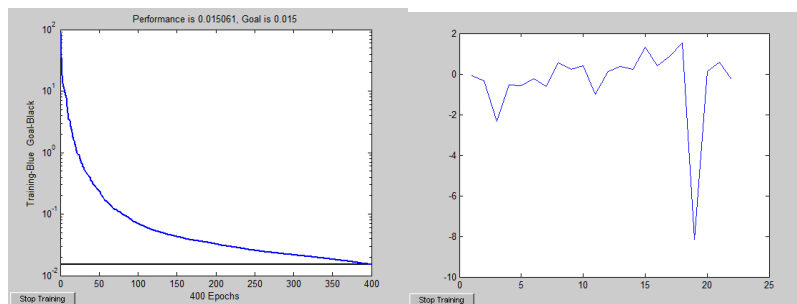


Figure 4.21 Training curve and Error curve of d5 RBF network

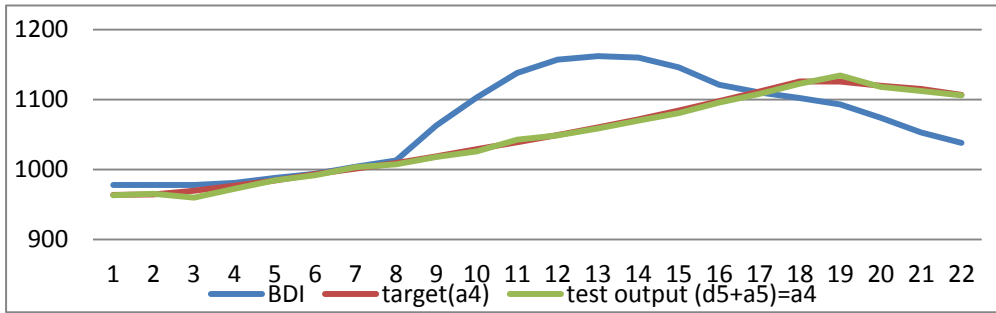


Figure 4.22 Comparison among network output a4, target, and original BDI

■ a3

It's the same procedure as a4. $a3' = a4' + d4'$.

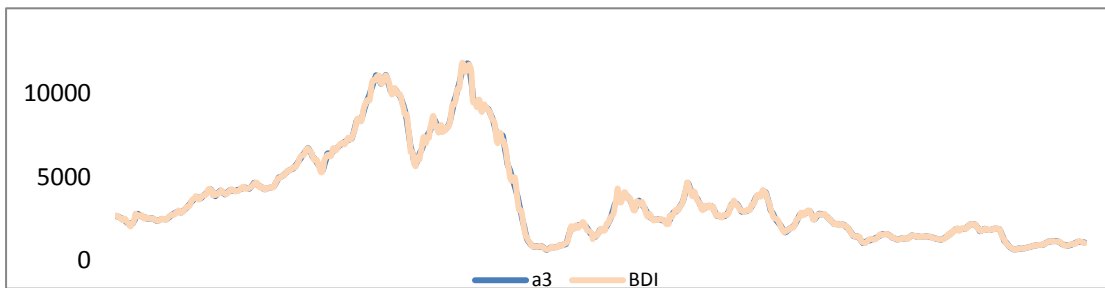


Figure 4.23 Comparison between reconstructed a3 curve and BDI

Training goal: 0.05 (400 epochs), spread rate: 1.5

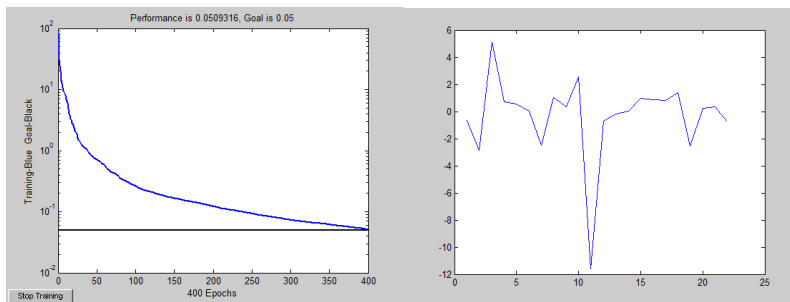


Figure 4.24 Training curve and Error curve of d4 RBF network

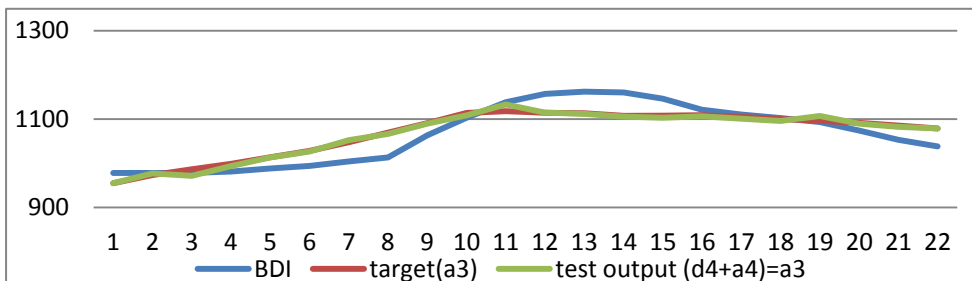


Figure 4.25 Comparison among network output a3, target, and original BDI

■ a2

It's same procedure as a4: $a2' = a3' + d3'$

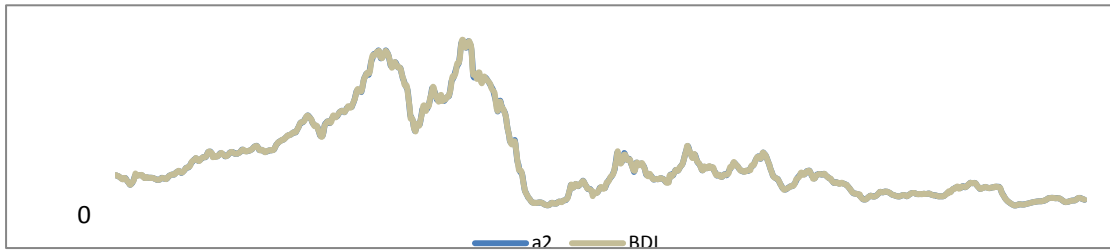


Figure 4.26 Comparison between reconstructed a2 curve and BDI

Training goal: 0.09 (375 epochs), spread rate: 1.5

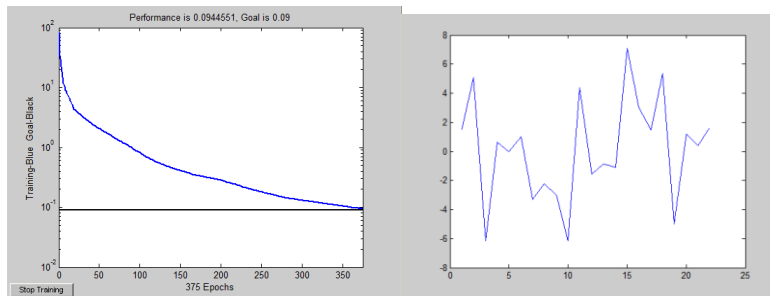


Figure 4.27 Training curve and Error curve of d3 RBF network

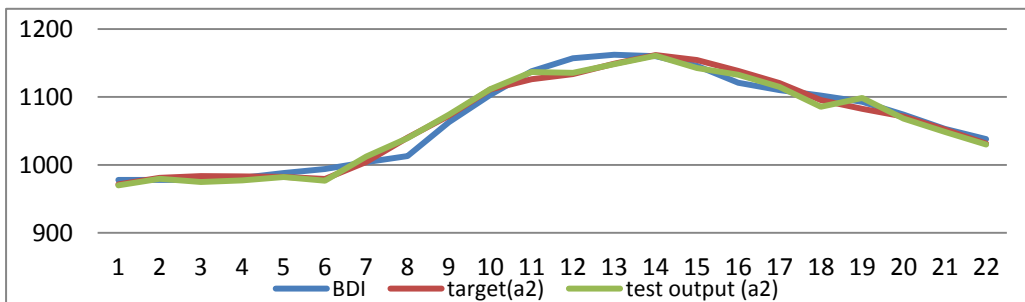


Figure 4.28 Comparison among network output a2, target, and original BDI

■ a1

It's the same procedure as previous step. $a1' = a2' + d2'$

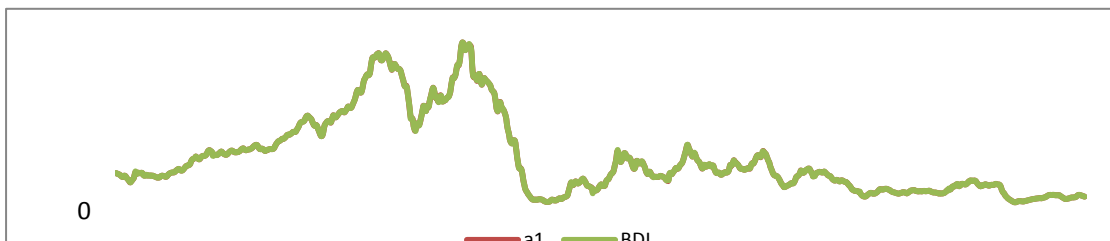


Figure 4.29 Comparison between reconstructed a1 curve and BDI

Training goal: 0.24 (400 epochs), spread rate: 1.5

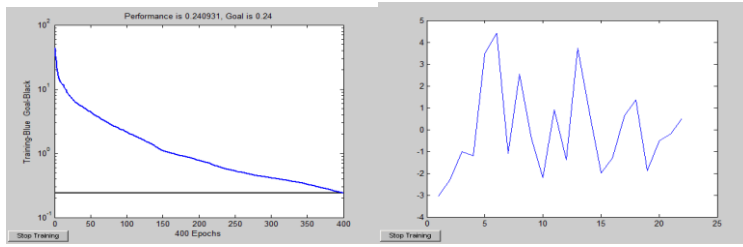


Figure 4.30 Training curve and Error curve of d2 RBF network

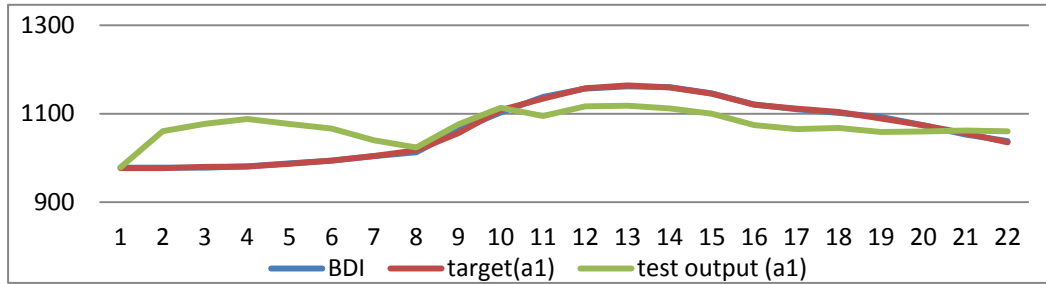


Figure 4.31 Comparison among network output a1, target, and original BDI

■ BDI

Due to the difference between the original BDI data and the reconstructed BDI is almost 0, so it can be considered that they overlap each other. So there is only one curve on the reconstruction graph and two curves on the test graph.

Training goal: 0.9^{22} (425 epochs), spread rate: 1.5.

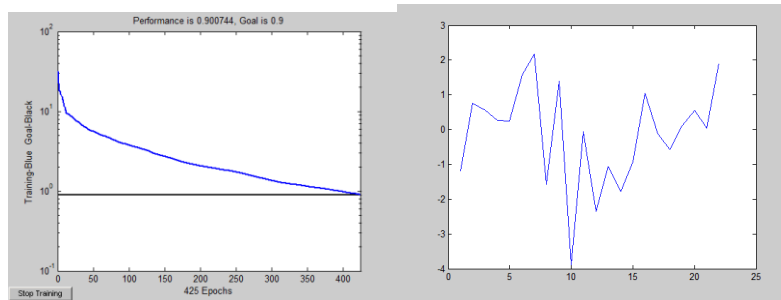
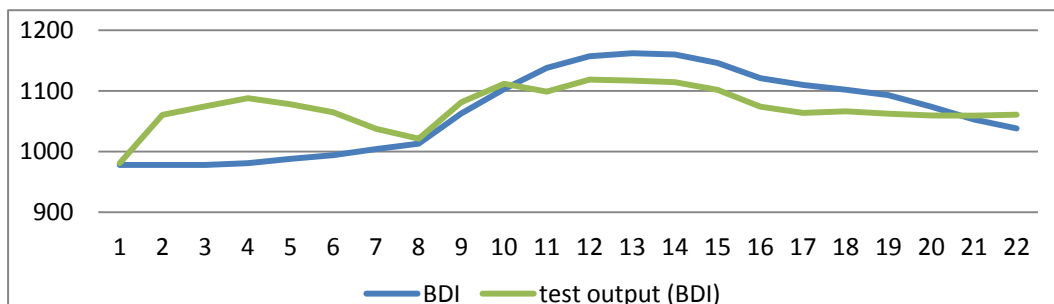


Figure 4.32 Training curve and Error curve of d1 RBF network



²² Due to the highest fluctuation of this high-frequency part, the goal has to be 0.9, otherwise, the network will spend 1 day or 2 days to achieve smaller goal, which will cause over training.

Figure 4.33 Comparison among network output, and original BDI

Mean Square Error (MSE) is adopted to evaluate each result, including the output MSE (between network output and filtered target) and curve MSE (showing the deviation, between filtered target and original data).

Table 4.2 Summary of Output error and Curve error

	Output MSE	Curve MSE	Summation
	Bigger value means bigger deviation between network output and filter data	Bigger value means bigger deviation between filtered data and original BDI	Deviation overall
a5	10.17146	6405.949	6416.121
a4	12.73316	2912.034	2924.767
a3	34.88545	940.9596	975.8451
a2	40.655	125.791	166.446
a1	2723.619	6.939013	2730.558
BDI	2667.223	0	2667.223

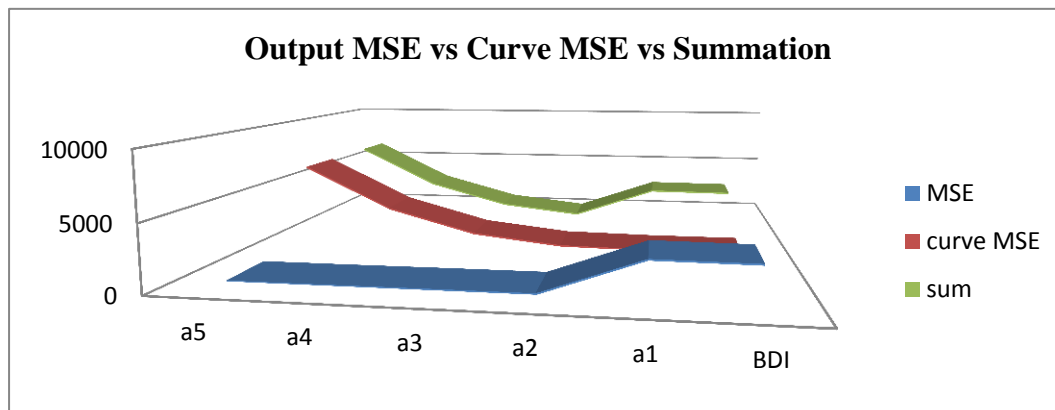


Figure 4.34 Illustration of output MSE, Curve MSE, and Summation

The blue belt shows that from a5 (only low-frequency part) to BDI (full combination of all-range frequency parts), the error between the outputs (a5', a4', a3', a2' and a1') and the targets (a5, a4, a3, a2, a1) becomes bigger and bigger, but obviously, with the introduction of more high-frequency parts (d5, d4, d3, d2 and d1), the error between the original data and filtered data will decrease significantly. So it comes to a problem

that if we want to make the filtered data approach the original data, we have to introduce more forecasting which will cause the performance of the network to decrease dramatically. So we focus on the summation of Output MSE and Curve MSE, another kind of mixture, and in the middle of the belt we get the optimal point (a2). So in this case, decomposition/reconstruction in the level of a2 will minimize the whole error deviation, including the filtered curve MSE and the output MSE.

4.3.4 Forecasting

Finally, the degree of de-noise/cleaning is fixed at a2 level, means a5, d5, d4, d3 are needed to reconstruct a2 due to $a2=a5+d5+d4+d3$.

Normally, ANN has better performance in short period forecasting, so the next 31 days, from 2012.7.23 to 2012.9.03. are forecasted.

Table 4.3 Forecasting BDI from 2012.7.23 to 2012.9.03

	a5 output	d5 output	d4 output	d3 output	Forecast a2
23-Jul	1054.9	44.218	-35.802	-36.892	1026
24-Jul	1053.2	37.445	-45.57	-18.239	1027
25-Jul	1048.6	28.418	-51.352	-1.9822	1024
26-Jul	1042.7	18.995	-54.919	22.308	1029
27-Jul	1040.1	10.877	-62.174	22.087	1011
30-Jul	1038.4	1.6455	-68.7	15.975	987
31-Jul	1035	-7.9309	-70.316	18.414	975
1-Aug	1031.8	-16.96	-69.171	14.722	960
2-Aug	1026.9	-26.337	-60.069	8.0111	949
3-Aug	1021.6	-35.361	-50.179	-0.48852	936
6-Aug	1018.1	-43.798	-40.163	-10.142	924
7-Aug	1015	-52.407	-27.206	-19.525	916
8-Aug	1013.2	-57.778	-7.6548	-12.561	935
9-Aug	1012.3	-61.638	18.494	-2.7629	966
10-Aug	1011.8	-66.454	44.814	1.5899	992
13-Aug	1011.6	-70.487	68.925	7.6265	1018
14-Aug	1012.6	-75.117	90.893	10.014	1038
15-Aug	1014.8	-79.415	111.44	11.978	1059
16-Aug	1017.5	-81.872	128.41	13.337	1077

17-Aug	1020.3	-83.818	138.34	13.541	1088
20-Aug	1020.8	-87.195	135.64	2.9226	1072
21-Aug	1019.8	-90.043	121.53	-8.4627	1043
22-Aug	1019.2	-91.435	103.05	-12.992	1018
23-Aug	1018.1	-91.786	82.505	-16.423	992
24-Aug	1016.8	-90.016	59.421	-12.077	974
27-Aug	1014.6	-87.407	37.94	-7.7955	957
28-Aug	1010.5	-84.325	17.714	-6.3397	938
29-Aug	1005.4	-79.57	-4.1667	-6.617	915
30-Aug	1000	-73.925	-29.297	-3.1421	894
31-Aug	994.2	-67.073	-57.755	2.1254	871
3-Sep	987.5	-58.637	-88.286	5.7539	846

*BDI is not published in weekend.

From the result of forecasting, BDI will remain in downturn in the next month.

4.4 Discussion

Forecasting always gives poor performance. In the last decade, researchers began to shift from the linear models to non-linear models because most cases in reality are very complicated. Among those emerging non-linear models, Artificial Neural Network, as an imitation of the human neural system, has become more and more important due to its effective performance. In this case study, ANN was combined with wavelet decomposition and each degree of de-noise was evaluated as an alternative way to ensure that the periodical character of the shipping market was accurately portrayed, preserving the useful information and removing the noise during the transformation. From the evaluation of each degree of decomposition, the performance of wavelet neural network varies like the shape of a “V”, and the trough point is the overall optimal point for this data forecasting. Although the classical regression model was not demonstrated to compare, the regular linear model cannot promise better performance in volatile data prediction in short time, and normally good at long-time and smooth data predicting.

CHAPTER 5

CASE STUDY 2: OPTIMIZATION OF THE NUMBER OF CONTAINER CRANES

5.1 Background: the overview of development of containerization

5.1.1 Containerization on the ship side

Six decades ago, the trucking company owner Malcolm Mclean worked with engineer Keith Tantlinger to develop the modern intermodal container. This design incorporated with a twist-lock mechanism to allow easy securing and lifting by cranes. And the first truly successful container shipping company dates to 1956. They deployed the SS Ideal X and sailed it, and the world came into the era of containerization.

In the 1960s, the container ships were going forward slowly. The size of those vessels was restricted to 500-1000TEU due to the capital stress and technical limit. But in the 1970s and 1980s, containerization came into the accumulation era, represented by the Panamax vessels. The ship design was limited by the dimension of lock chambers in the Panama Canal. The capacity of these ships reached the limitation of 2000-3000TEU.

From the early 1990s, the 4th generation container ship emerged. The pioneer shipping lines decided to abandon the restriction of the Panama Canal, and they developed the Post-Panama vessel, whose breath exceeds the width of the Panama Canal (32.3 meters).

In 2006, Maersk line deployed the E-class vessels, whose capacity is around

13600TEU. And in 2011, it invested to build the new triple-E class vessel²³ (length: 400M, beam: 59M, draft: 14.5M). And its capacity hit 18000TEU.

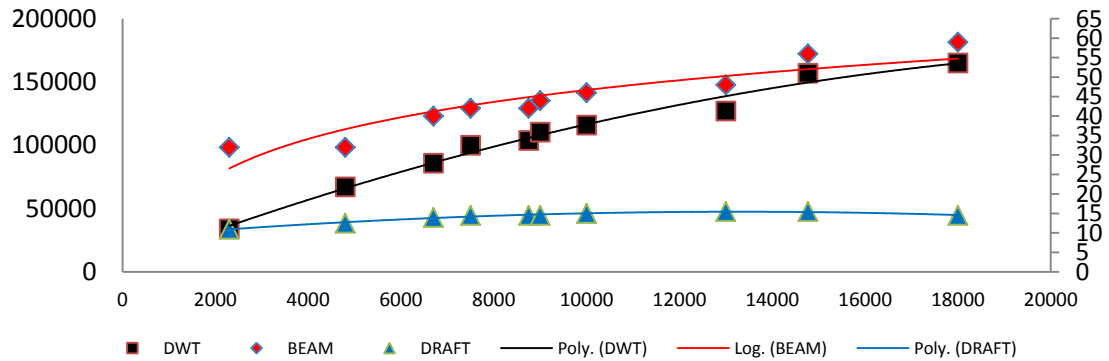


Figure 5.1 Development of Container ship size

Source: Various sources of ship dimension

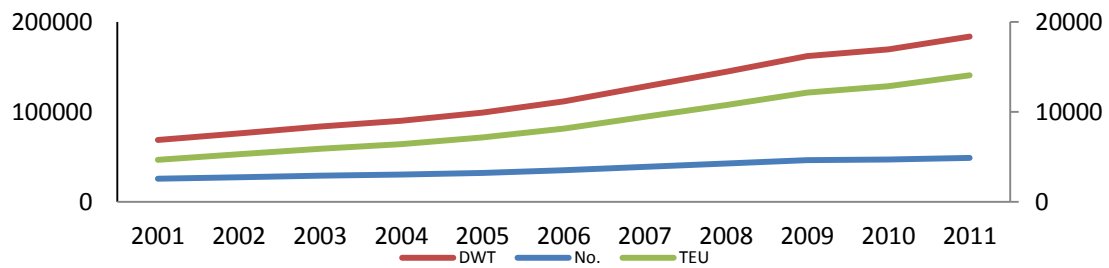
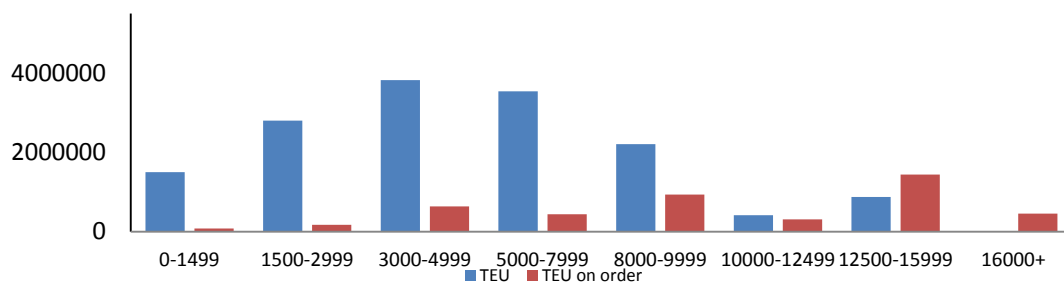


Figure 5.2 Container ship number, DWT, TEU capacity development

Source: data collected from *shipping statistics yearbook 2011*

As mentioned before, the size of newly delivered container vessels continued to expand, resulting in an increase in the average capacity of container ships. From the graph, it is clear that TEU increased much faster than the number of ships, just because of the bigger and bigger size.



²³ Maersk Triple-E class container vessel. Retrieved from http://en.wikipedia.org/wiki/Maersk_Triple_E_class

Figure 5.3 The Capacity of container fleet and new building vessels, 2011-September

Source: Data collected from *International containerization year book 2012*

After the financial crisis, the container trade reported huge losses in 2009, but in 2010, international trade rebounded back due to cutting down too much supply and increasing demand, showing the strongest recorded growth rate in history. In 2011, and first half of 2012, the imbalance between demand and supply drove the freight down again. Although the giant China slows down the pace of development, making the situation more severe, it is apparent in the past 2 decades, container trade still grows at around 8% per annum.

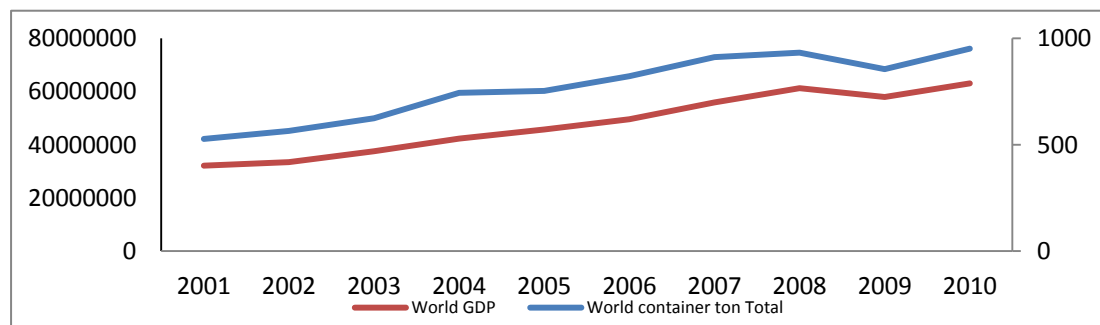


Figure 5.4 World container trade (tonnage) and GDP

Source: Data collected from UNCTAD statistics and *shipping statistics yearbook 2011*

Besides, the container market is rather concentrated. The top 15 shipping lines control 72.5% of the total container fleet²⁴, showing a high concentration of the market. Another interesting fact is the strongest shipping lines also are the dominant international port operators. In addition to the aggressive expansion of fleet, they also form several super shipping lines alliances against each other.

5.1.2 Containerization on the port side

Increasing container shipment stimulates the development of container terminals, logistics, and management after financial crisis. And this development also results in increasing competition between the neighbor ports, especially in the Hub-Spoke

²⁴ Further information can be found in <http://www.alphaliner.com/top100/index.php>

transshipment business. As mentioned before, the container shipping market is rather concentrated, which means the shipping lines are so strong that they can even contend with the ports. Once they are not satisfied with the performance of the port service, they can quit from that port, and transfer to a neighboring port. With the recovery of the throughput, the problem gradually emerges: how to keep and increase the current throughput and attract more shipping lines?

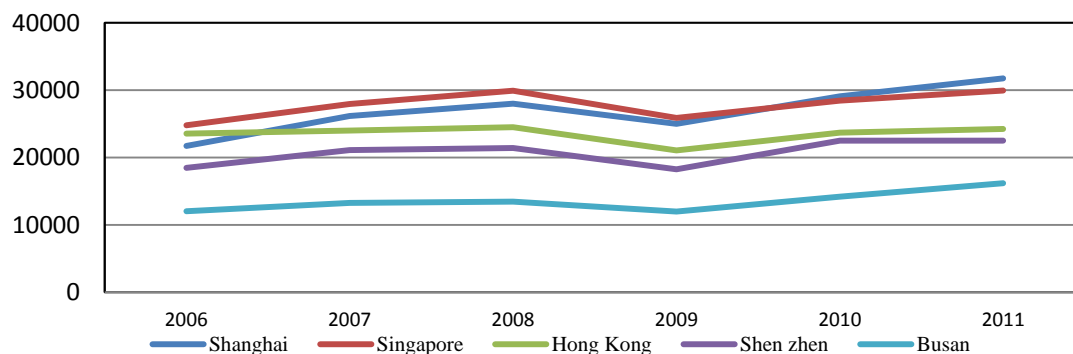


Figure 5.5 Top 5 container port throughput from 2006 to 2011, 1000TEU

Source: Data collected from *International containerization yearbook 2007-2012*

As a container terminal, the aim should be that the ship on arrival can get a berth, and container handling should be done in an efficient, smooth way. But due to the irregular arrival of ships and unexpected problems in cargo handling/transiting/storage, the ships sometimes have to suffer from delays, causing loss of freight and customers. In “The time factor in liner shipping services” by T. Notteboom, he found that in East Asia 65.5% of delays are due to port congestion, the second problem is lower than expected terminal productivity.²⁵

So the port side will consider expanding the current terminals to satisfy the shipping lines, but investment in new terminals undergoes potential risks.

Due to the virtual terminal, throughput forecasting will be blind, which will lead to wasting / insufficient investment after construction. Although there exists traditional port planning frameworks, all the sub-titles are selected by humans, thereby containing strong subjective intention, or qualified advice. In order to avoid the

²⁵ The data can be found in Figure 5. Notteboom T. (2006). The time factor in liner shipping service. *Maritime Economics & Logistics*, 8:1, (pp 19-39)

subjective influence, quantitative methods are needed to give objective answers, learning from other terminals, so a DEA related method will be suitable to estimate.

5.2 The given specification of the new container terminal and Goal

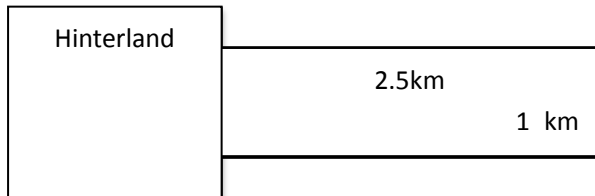


Figure 5.6 Specification of given terminal area

Source Pro. Aykut

The terminal contains 2.5km X 1km land, and the maneuvering area is 3km x 2.5km. Port land includes circulation space, but space for supporting services is not necessary.

The goal has been mentioned in Chapter 1: **find the optimal and practical crane number to achieve the highest efficiency of the port.**

5.3 The application of DEA-Artificial neural network model

5.3.1 The overview of DEA-BP model

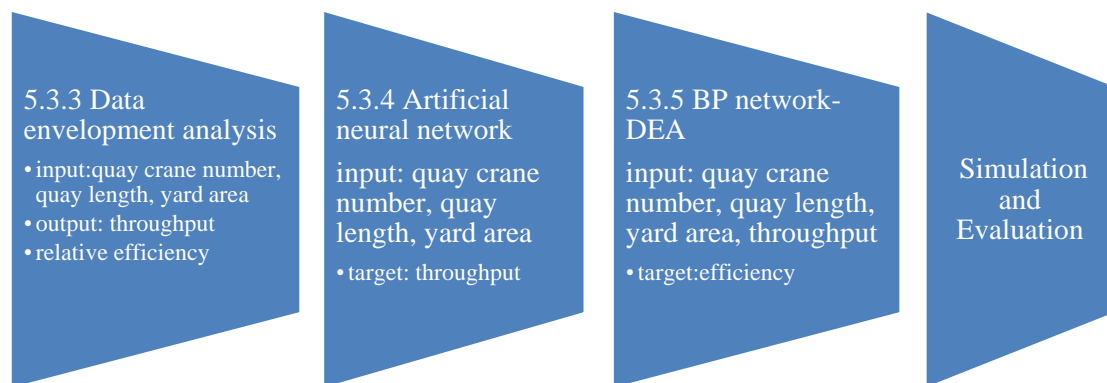


Figure 5.7 The procedure of DEA-BP model

5.3.2 Data collection and analysis

In data collection, it should be noticed that the wrong data inevitably will lead to the wrong conclusion, and the selection of variables should reflect the direct relationship

between inputs and outputs. From the literature review, it was found that the previous studies focused on various inputs and outputs due to the availability of the data. Generally, the port will not post detailed specifications of their terminals, only leaving the general data. But to some degree, they have to show shipping lines their facilities, which allows the collection of some data from “Containerization international year book” from 1985, covering various port information.

It was decided to employ 3 inputs and 1 output, expressing the basic function of a terminal.

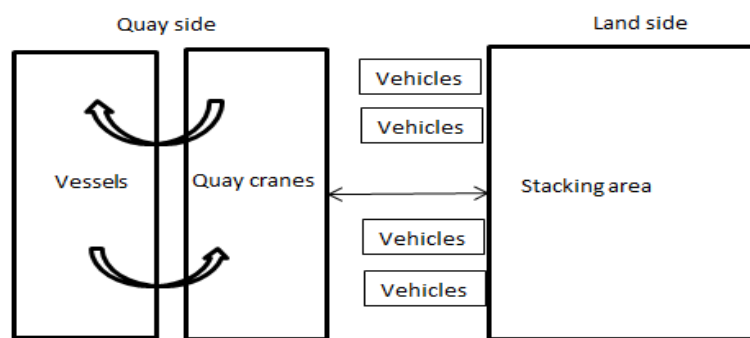


Figure 5.8 Brief illustrations of container terminals

- 3 Inputs:

- Quay crane number

The crane number definitely stands for the productivity of terminals. But in the year book, different ports have various combinations of cranes, including Super-Post-Panamax crane (more than 22 row wide), Post-Panamax crane (about 18 row wide), Panamax crane (12-13 row wide), mobile crane, and feeder cranes. What is more, some ports do not even give the specification of the cranes: only showing “total XX cranes”. Although the cranes are not unified, we can deliberately choose those ‘big’ ports which have a throughput exceeding 500 000TEU. The reason is that those big international container ports on behalf of the country gateway normally will be equipped with the modern and unified facilities.

Finally, the summation of cranes in each container terminals is made, standing for each quay crane number.

- Quay length

Collecting data on quay length does not pose many problems. The only problem is

“shared quay length”. In some ports, the general cargo berth, multiple-purpose cargo berth and container cargo berth are mixed, meaning the berth is not always occupied by container cargo. In this case, we try to avoid those mixed terminals, and the good thing is that most modern, large container terminals are dedicated to containers.

A summation is made of the quay length of each container terminal.

- Yard area

The size of yard area depends on the nature of the port, dwell time, and technical factors. Generally, the bigger the yard area, the larger storage is. But the different kinds of yard facilities also decide the capacity, especially for the yard gantry crane. According to the year book, some ports have extremely high utilization of yard area, and for example, Singapore, and some ports have very low utilization. But low utilization does not mean low efficiency; for example, dangerous cargo needs more clearance, and heavy containers cannot be stacked as high as empty containers.

The yard area is collected in h.a./10000 m²

- 1 output: Throughput

Container throughput is definitely the most important output of container terminals. Almost all the previous studies use it as the output because it is the direct aim and basis, which can be compared among those terminals, and throughput is related to the revenue of the terminals.

- Other variables

Of course, there are other facilities in the container terminals: trucks, AGV, straddle carrier, and yard gantry crane. Different ports have different combinations, for example, Hamburg port adopts the AGV - Automatic yard crane, but most Chinese ports use labor-intensive methods: trucks - manned yard cranes. And the selection of combination depends on the cost-revenue analysis. Because the model is based on the assumption of the same technology, we cannot involve the different parts in the system. But it should be realized that in most container terminals, the operation is still based on human, the same technology. Besides, many other variables also affect ship efficiency, not only the physical labor and facilities, but also the virtual indicators,

like occupancy, and utilization. But due to availability of data, those cannot be adopted.

Table 5.1 Statistical description of the container terminals

	QUAY CRANES	QUAY LENGTH	YARD AREA	THROUGHPUT
Mean	17.5	1949.2	87.6	2451112.5
Standard Error	1.54	190.72	7.07	257717.46
Median	12	1494	79	1760376
Mode	10	1180	37	#N/A
Standard Deviation	10.3058	1279.3904	47.4272	1728821
Sample Variance	106.2101	1636839.7222	2249.336	2988823047484
Kurtosis	0.6420	13.0157	2.5602	-0.3934
Skewness	1.0127	2.9637	1.4677	0.9703
Range	44	7650	215.1	5536000
Minimum	5	650	20.9	564000
Maximum	49	8300	236	6100000
Sum	788	87715	3944.157	110300062
Count	46	46	46	46

5.3.3 The efficiency ranking of the terminals by applying DEA model

The DEA SOLVER 3.0, student version, is adopted to process the data. Quay crane number, quay length, and yard area are used as the inputs, and the throughput as the output. After calculation, it returns the CRS result and VRS result, we can compare the 2 different rankings.

Table 5.2 Ranking of container terminals (CCR and BCC)

No	DMU	CCR-Score	CCR-Rank	BCC-Score	BCC-Rank
1	ALGECIRAS-APMT-SPAN	0.919472	13	0.9344904	16
2	ANTWERP-PSA-BELGIUM-EUROPA	0.5551052	25	0.7368165	25
3	ANTWERP-PSA-BELGIUM-NOORDZEE	0.4516042	39	0.558919	37
4	BREMERHAVEN-APMT-GERMANY	0.8902637	15	0.8916169	17
5	CHARLESTON-SSA-USA	0.5294214	28	0.6173973	30
6	DUBAI-DPW-UAE-JEBEL ALI	0.9646676	8	1	1
7	DUBAI-DPW-UAE-PORT RASHID	0.6626658	21	0.7519186	24

8	FELIXSTOWE-HPH-UK	0.4831633	35	0.501345	45
9	FREEPORT-HPH-BAHAMA	0.5558016	24	0.6483132	28
10	GIOIA TAURO-APMT-ITALY	0.7482154	19	0.780782	20
11	ALTENWEDER-HHLA-GERMANY	0.6077797	22	0.6586539	26
12	BURCHARDKAI-HHLA-GERMANY	0.5373572	27	0.5512135	40
13	HONGKONG-HPH	0.9357426	12	1	1
14	KAOHSIUNG-APMT-TAIWAN	1	1	1	1
15	LONGBEACH-SSA-USA	0.3806173	42	0.6038424	31
16	LOS ANGELES-SSA-USA	0.5088063	32	0.5710874	34
17	MANILA-MICT-PHILIPPINES	0.5204756	29	0.5696359	35
18	NEWARK-DPW-USA	0.4786189	37	0.7771831	22
19	PORT ELISABETH-APMT-USA	0.3202277	46	0.5096641	43
20	QINGDAO-APMT-PRC	0.9986092	6	1	1
21	RAYSUT/SALAH-APMT-OMAN	1	1	1	1
22	ROTTERDAM-APMT	0.8106512	16	0.8114762	19
23	ROTTERDAM-HPH	0.6815747	20	0.7805107	21
24	SHANGHAI-APMT-PRC	0.5971723	23	0.6344758	29
25	SHANGHAI-HPH-PRC	0.944285	11	0.9729422	15
26	SINGAPORE-PSA-BRANI	1	1	1	1
27	SINGAPORE-PSA-KEPPEI	0.9164341	14	1	1
28	SINGAPORE-PSA-PASIR PANJANG	0.9921693	7	0.9927887	14
29	SINGAPORE-PSA-TANJONG PAGA	1	1	1	1
30	TANJUN PELEPAS-APMT-MALASIA	0.7516152	18	0.7679371	23
31	TANJUN PRIOK-HPH-INDONESIA	0.4815028	36	0.5079551	44
32	TANJUN-HPH-INDONESIA	0.4682183	38	1	1
33	YOKOHAMA-APMT-JAPAN	0.4962431	34	1	1
34	jasungdae container terminal-S.KOREA(2010)	0.3735579	44	0.5291517	42
35	Korea express busan terminal-S.KOREA(2010)	0.953484	9	1	1
36	Pusan new port-S.KOREA(2010)	0.9496079	10	1	1
37	sin gamman container terminal-S.KOREA(2010)	0.7598648	17	0.8262419	18
38	Ningbo-PRC(2010)	1	1	1	1
39	gateway deuganck dock berths (2010)	0.3459448	45	0.5941711	32
40	MSC home terminal-Belgium(2009)	0.5167808	31	0.5293078	41
41	Leon y castillo dock-FRANCE(2009)	0.5042272	33	0.5766327	33
42	FOS container terminal-FRANCE(2010)	0.3777255	43	0.6497933	27
43	North sea terminal Bremerhaven gmbh & Co-GERMANY(2010)	0.4412146	40	0.4645841	46
44	Voltri Terminal-ITALY(2010)	0.3978406	41	0.5646635	36

45	APM terminals algeciras sa-SPAIN(2009)	0.518444	30	0.5566561	39
46	Noatum container terminal valencia-SPAIN(2010)	0.5420561	26	0.5584609	38

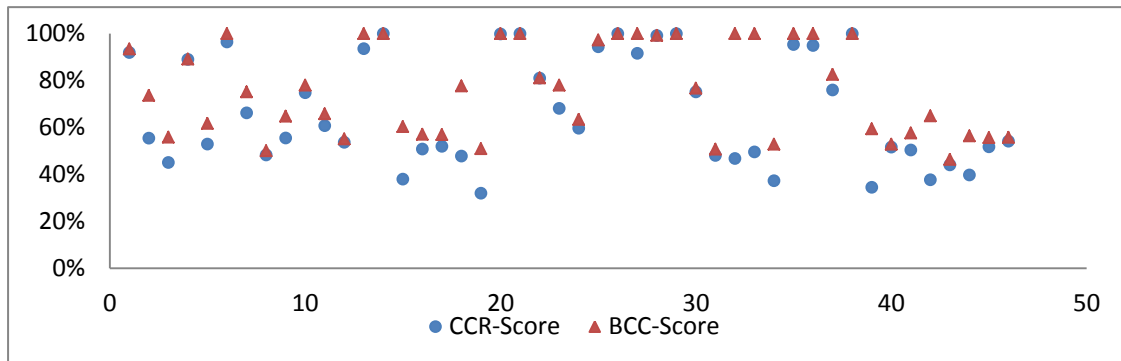


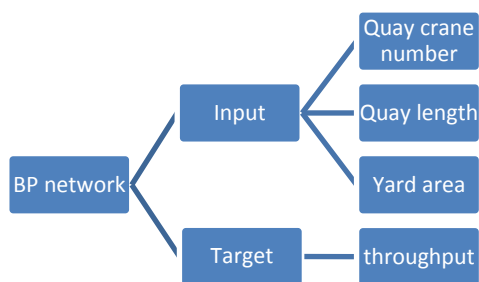
Figure 5.9 Container terminals efficiency ranking: CCR V.s BCC

It's clear that BCC-efficiency is normally higher than CCR-efficiency, because CCR-efficiency is technical efficiency, regardless of the decrease of return of scale, which BCC will consider.

5.3.4 Forecasting of terminal throughput by applying BP network

- **The selection of inputs and target, and training**

In the DEA part, a brief introduction of several variables was given, including quay crane number, quay length, yard area, and throughput. Due to the problem of availability and unification of data, it was not possible to collect any other non-standard data, but it is revealed that the crane number and quay length guarantee



the productivity, and the yard area decides the storage in the container flow. Although these data may not be sufficient to describe the whole character of a port, they must be strongly related to the throughput.

Figure 5.10 Selection of Inputs and Targets in BP network

The 46 groups of data are divided into 2 sections: 41 groups as training data, and 5 random groups as the test data.

In this case, 3 layers BP network (3-10-1) is employed: 3 neurons in the input layer, 10 neurons²⁶ in the hidden layer, and 1 neuron in the output layer. Training function is LEARNLM. The transfer function in the hidden layer is TAGSIN, and transfer function in the output layer is PURELIN.

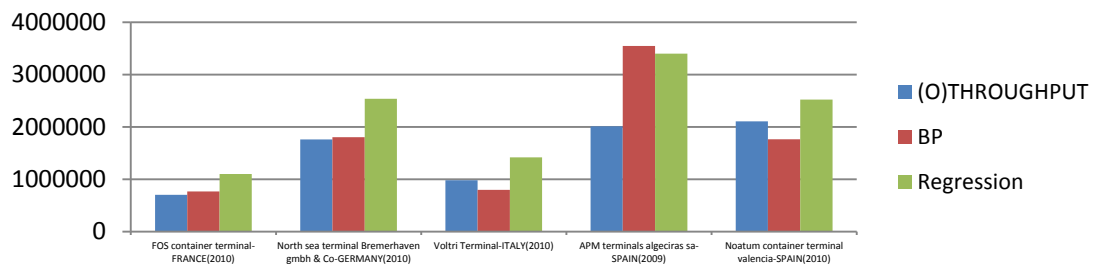
Other parameters are default, except the epoch limit: 10000 times. When it repeats training around 3000 times, the training curve is almost flat, showing no room to improve. So it is stopped.

● **Evaluation of the output**

Five groups were randomly chosen as the test group, and the remaining groups were considered as the training groups. Besides, multiple-regression was used as naïve model to compare the outputs. (M-Regression: variables: quay crane number, quay length, and the dependent variable is throughput, **the yard area was abandoned** due to its 95% confidence not qualified).

Table 5.3 Throughput Simulation based on BP network and M-regression models

Terminals	(I)QUAY CRANES	(I)QUAY LENGTH	(I)YARD AREA	(O)THROUG HPUT	BP	M-regression
FOS container terminal-FRANCE(2010)	8	1180	56.00	703000	766800	1102552
North sea terminal Bremerhaven gmbh & Co-GERMANY(2010)	18	1829	108.60	1760376	1805000	2538330
Voltri Terminal-ITALY(2010)	10	1400	85.00	980939	798980	1419209
APM terminals algeciras sa-SPAIN(2009)	25	1846	66.73	2013635	3549000	3400348
Noatum container terminal valencia-SPAIN(2010)	18	1780	106.00	2108737	1765100	2522304



²⁶ The hidden neuron number varies, depending on the each performance or experience. 10 neuron is just fine

Figure 5.11 Comparison among outputs based on BP network and M-regression

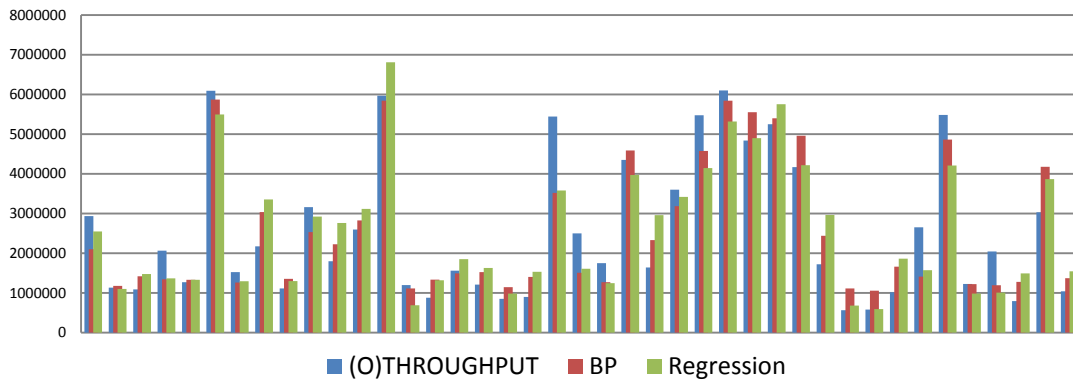


Figure 5.12 Comparison of throughput simulation based on BP network and M-regression

The MSE of all results was calculated, and MSE-BP was $4.23E+11$, and M-regression-MSE was $5.53E+11$. In most cases, the results of BP network are generally satisfied. The biggest individual deviation of test is in the group of “APM terminals Algeciras sa-SPAIN (2009)”, the reasons may be:

- ◆ Absolutely different type of the port. The facilities of the import/output oriented port will be significantly different from those of the transiting oriented ports. Solution: introduce advanced new algorithms and more comprehensive training data.
- ◆ If one variable is too outstanding, it will confuse the network. Solution: collect enough data or introduce classification of different aim of ports.

● **Forecasting the capacity of different combination of crane number**

The trained network has been obtained, and it can be applied to the different combination of quay crane numbers. Due to the fact that the specification of the berth is fixed, we know that the total quay length is 6000 meters, and the yard area is 150 h.a. But as it was mentioned that the extremums will confuse the neural network, it was decided to divide the berth into two equal parts: 3000 meters length, and 125 h.a. area

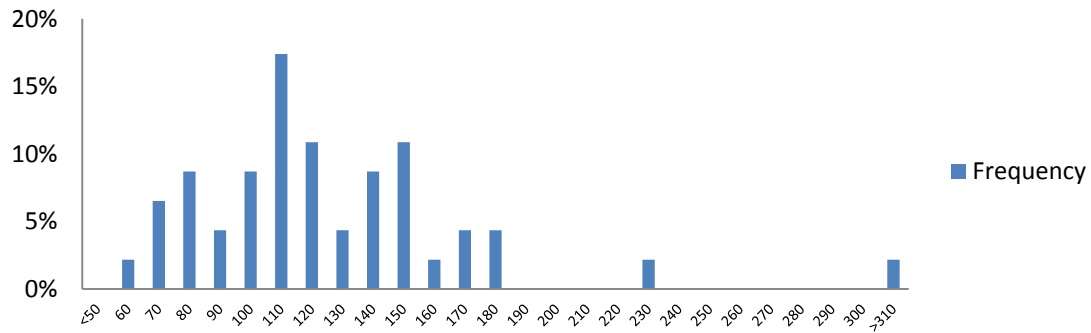


Figure 5.13 Interval of cranes counting

In order to obtain a reasonable range of crane numbers, we count the quay crane intervals of 46 terminals. The graph shows that most intervals of cranes fall in “110 meters”, but there are also extremely close intervals of 60 meters, which may result from the dense feeder cranes.

So in our possible combinations, the crane number starts from 25 (120m/crane) to 40 (75m/crane). The table shows the output from the neural network.

Table 5.4 The Throughputs of each combination (25-40 cranes) based on BP network and M-regression models

Quay crane number	Quay length	Yard area	Throughput-BP	Throughput-M-regression
25	3000	125	4.01E+06	3777783
26	3000	125	4.32E+06	3900134
27	3000	125	4.64E+06	4022485
28	3000	125	4.95E+06	4144836
29	3000	125	5.25E+06	4267188
30	3000	125	5.53E+06	4389539
31	3000	125	5.79E+06	4511890
32	3000	125	6.02E+06	4634241
33	3000	125	6.22E+06	4756592
34	3000	125	6.38E+06	4878943
35	3000	125	6.50E+06	5001294
36	3000	125	6.59E+06	5123645
37	3000	125	6.64E+06	5245997
38	3000	125	6.65E+06	5368348

39	3000	125	6.62E+06	5490699
40	3000	125	6.55E+06	5613050

The interesting thing is when the crane number is 38, the throughput reaches the maximum value among all the data in BP network model, but in the M-regression model, it seems that the more cranes, the more throughput is achieved. It can be explained that Neural Network remembers the pattern of each training input and output, or the internal non-linear relationship, in other words, only a specific combination which meets the pattern of input can achieve the best performance/output. But for M-regression, it is linear relationship, ignoring the internal relation between each variable.

5.3.5 Searching the optimal number of crane by applying DEA-BP model

The **CCR score** of each terminal and each capacity of different crane number have been obtained, the score or efficiency can be considered as the target of the network, and the quay crane number, quay length, yard area, forecasted capacity as inputs.

- 4-10-1 structure²⁷
- Training function: LEARNLM
- Transfer function in hidden layer: TAGSIN
- Transfer function in output layer: PURELIN
- The setting of training is default except the epoch limit set to 10000 times.
- When it repeats 550 times, the stop condition is satisfied (goal =0).

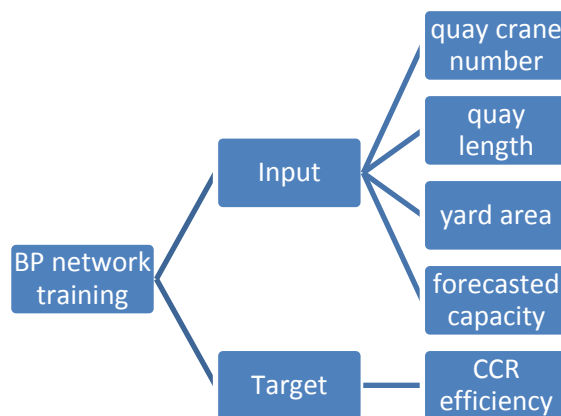


Figure 5.14 Selection of Input and targets in BP-DEA model

²⁷ From experience.

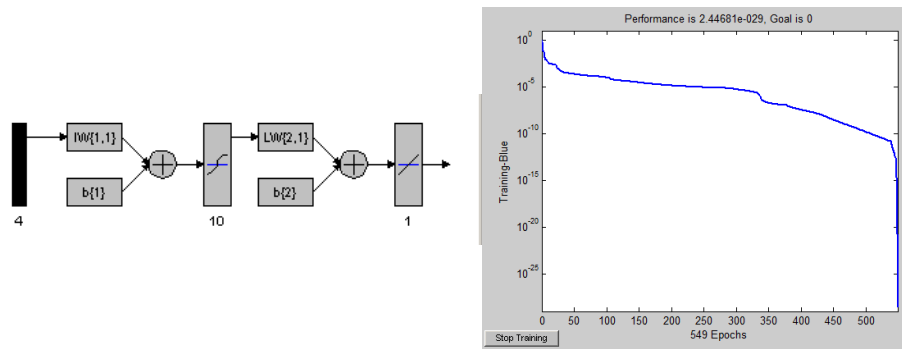


Figure 5.15 Structure of BP-DEA model and training curve by MATLAB

When it repeats 550 times, the stop condition is satisfied (goal =0).

The data in the **table 5.5** are used as the inputs, and applied to the trained network, so the output can be obtained. In order to compare, M-regression is introduced again to compare the efficiency (All variables are 95% significant, qualified. And R square is 0.7983).

Table 5.5 Simulated efficiency of each combination (25-40 cranes) based on BP network and M-regression models

Quay crane number	Quay length meter	Yard area h.a.	Throughput TEU	BP	M-regression	Density meter
25	3000	125	4011800	0.84335	0.801446	120
26	3000	125	4321900	0.97043	0.855735	115
27	3000	125	4637900	1.0345	0.911405	111
28	3000	125	4950600	1.0404	0.966302	107
29	3000	125	5251700	1.0187	1.018484	103
30	3000	125	5533900	1.0003	1.066244	100
31	3000	125	5791400	0.99622	1.108222	97
32	3000	125	6019900	1.0025	1.143414	94
33	3000	125	6216000	1.0122	1.171023	91
34	3000	125	6377200	1.0208	1.190464	88
35	3000	125	6501800	1.0264	1.201339	86
36	3000	125	6588600	1.0287	1.203368	83
37	3000	125	6636600	1.0282	1.196316	81
38	3000	125	6645500	1.0255	1.180114	79

39	3000	125	6615200	1.0213	1.154737	77
40	3000	125	6546000	1.0159	1.120256	75

5.3.6 Discussion

- Efficiency > 1

The efficiency obtained from BP network exceeds 1 because some throughputs (crane number 33-40, the throughput exceeds 6100000) as the input are more than the original maximum throughput in the original DEA model, causing the desired efficiency to exceed 1. Besides, it is relatively efficient in terms of how much it is accounted for by measuring the proportion between its output and the frontier. Because in this case, the previous DEA score ranking established the frontier, so when another more efficient pattern of input/output comes into model, it will accordingly give the Ultra-efficiency.

- 2 peaks

It is noticed that when crane **number=28** with throughput=4950600, the efficiency reaches 1.0404, which is the highest in the BP network, but 0.9663 low in M-regression model. When crane **number=36** with throughput=6588600, the efficiency achieves 1.0287, which is 3rd high in BP network, but 1.2034 highest in M-regression model.

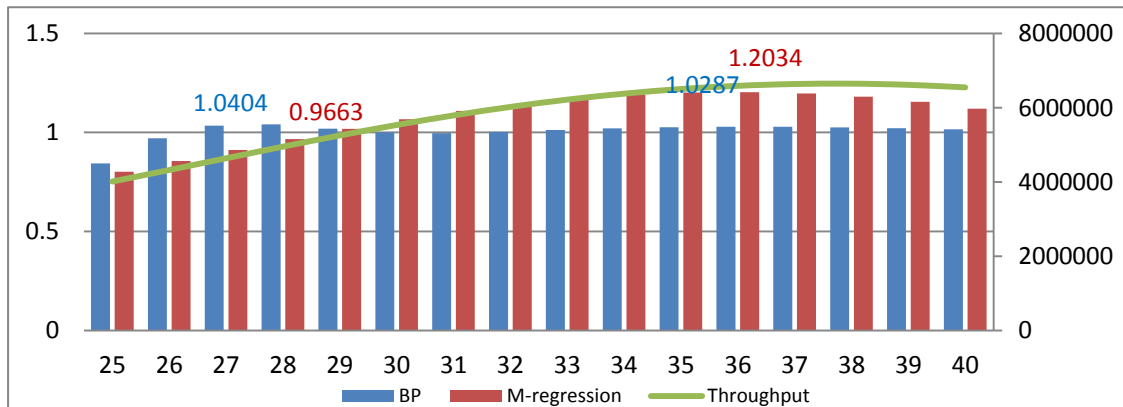


Figure 5.16 output of efficiency of each combination based on BP network and M-regression and Throughput

In the previous section, we can find within the range 25-40 cranes, the maximum capacity is 6645500 (crane number=38). From the practical view, interval: 83M (36

cranes) and 107M (28 cranes) are all feasible, but for a port, if they can increase the throughput by 1.638M (6588600-4950600), they will choose 36 cranes instead of 28 cranes, because the throughput directly reflects the revenue. In addition, from 28 to 36 cranes, throughputs increase by 204750/crane p.a. $((6588600-4950600)/8 \text{ cranes})$, but from 36 to 38 cranes, throughput only increases 28450/crane p.a. $((6645500-6588600)/2 \text{ cranes})$.

5.3.7 The final optimal combination

After discussion of the two possible efficient peaks, it is better to choose the 36 cranes combination:

Table 5.6 Final optimal combination

Quay crane number	Quay length	Yard area	throughput
36	3000 meters	125 h.a.	6588600 TEU
36	3000 meters	125 h.a.	6588600 TEU

So in the given area, total **72 quay cranes**, 6000 meter quay length, and 250 h.a. yard areas can hold the capacity of 13 177 200TEU per annum., achieving the highest efficiency.

CHAPTER 6

CONCLUSION AND RECOMMENDATION

6.1 Forecasting Baltic Dry Index

- **Conclusion**

At first, the global shipping market was briefly reviewed and the dry bulk shipping market was also introduced in order to give the general idea of the dry bulk market. Then by presenting the demand and supply of the dry bulk market, it is clear that the freight index of the dry bulk market is a result of interaction between demand and supply. But the demand and supply are influenced by a lot of factors, which frequently bring huge disturbances to the freight market. For shipping companies, they have to face high risks and uncertainty. So the industry needs forecasting to withstand, reducing loss.

Secondly, in the high fluctuating dry bulk market, Stopford finds that cyclical factors exist. He breaks down the freight rate in terms of classical decomposition, including long term trends, seasonal trends, and irregular trends. And this decomposition becomes the foundation of application of wavelet-decomposition. (The Fourier transfer, as the father of wavelet transfer is firstly introduced, followed by wavelet transformation in the methodology). After comparison among different wavelets, db3, 5 wavelet was chosen to decompose BDI, and obtain a5 (low –frequency part), d1-d5 (different scales of high-frequency parts). Although the raw data needs to be filtered to reduce the interference of the “noise”, the question is how much the data should be filtered / cleaned. Excessive filtering will eliminate the useful information in the data, but insufficient filtering will leave too much noise, confusing the model. In order to evaluate the suitability of de-noise, a5, d1-d5 were treated as the inputs and target in

each individual RBF neural network, and after training, a_5' , a_4' , a_3' , a_2' , a_1' , and “BDI’” (this is reconstructed BDI, not the original one) were reconstructed, following the sequence of “high degree of de-noise to low degree of de-noise”. Then the error between a_5 and a_5' , a_4 and a_4' , a_3 and a_3' , a_2 and a_2' , a_1 and a_1' , BDI and BDI’ were calculated. At same time, every time the forecasted higher-frequency part was added to “low-frequency part” in order to obtain a new combination of “low-frequency part” will contribute to accumulation of error, but the new combination of “low-frequency part” will gradually approach to the original BDI. Finally, the 6 outputs were summarized in terms of different degrees of de-noise, by calculating the summation of Output error and Curve Error. The a_2 degree of de-noise shows the best performance, including efficiently training neural network and compromised deviation between reconstructed curve and original curve. The RBF neural network provides reliable generalization and learning ability, which is satisfied. Then “ a_2 degree of de-noise” ANN was employed to forecast the BDI in the next 31 days²⁸, which shows BDI will still follow the downturn trend.

In the current dry bulk market, the shipping company can benefit from the reliable forecasting tool, dealing with the complex, non-linear freight rates or other index. The forecasting information is a sign of early warning, helping people to make decisions in the future. For the maritime industry, this wavelet neural network also can be adopted in other fields instead of freight rate/index.

- Recommendation

- Tuning

It should be noticed that different training populations will bring different output. In the present case, in order to cover the comprehensive information, 1548 groups of data were set as training population, and the last 22 groups of data were set as testing population. But in practice, more training populations do not mean a better trained network, because some “garbage” data will confuse the network. So in further studies, the training data needs to be identified by evaluating each individual performance.

- Introducing other algorithms

²⁸ It means 31 working days, from Monday to Friday.

New Algorithms can contribute a more efficient and better model. For example, in theory, the genetic algorithm can improve the performance of BP network by optimizing the weight. But in practice, performance is influenced by a lot of factors. New algorithm also may foul the network. So in further study, let the facts speak.

- Standard access

In this study, all the calculations and transformations are based on Excel and MATLAB, but the operation of commands was done manually, with lack of access between each component. So in the future, based on this method, a new integrated system can be developed to process the data automatically without human intervention.

6.2 Optimization of the number of container cranes

- **Conclusion**

Firstly, in the development of global containerization, the challenges to ports increased gradually, including the contrast between shipping lines` expectations and congestion in ports, and fiercer competition against neighboring ports. So expansion of new terminals is a good idea. Investment in new terminals is completely different from expansion of an existing terminal because the known terminal can provide all the data required by simulation programs. The simulation program will figure out the “gooseneck” of the current system, and the expansion can be guided in terms of balancing each component. In contrast, new terminal planning has to go forward in the dark.

Secondly, because investment in new terminals contains high uncertainty, a practical and efficient tool is needed to measure the performance of ports based on the known data. So DEA, as an efficient tool to measure relative efficiency, is combined with Artificial Neural Network, which provides effective ability of simulation. By training BP network with 46 groups of data, the throughput for each different number of cranes was estimated. Then another BP network was created to simulate the input/throughput-efficiency pattern. After full training of the 2nd BP network, the input/estimated throughput was input into the model so as to get estimated efficiency.

After discussion of the result, the practical optimal option was chosen to achieve the best throughput and efficiency.

This combination method can give better performance, compared to a pure linear program DEA model, especially in a large population.

- Recommendations

- Classification of ports

As mentioned before, the main business of the port will affect the structure of terminals. In further studies, it is better to classify the ports into several categories based on the main cargo: regional hub ports, feeder ports, and mix of the two previous ports. And 3 individual networks should be **clearly** trained by 3 different kinds of ports, focusing on different cargo.

- Multiple goals

Because the networks in this case study are all single output, in fact, the ANN can also solve multiple-goal problems. So in further studies, this model can be applied to complicated situations, which contain multiple goals.

REFERENCE LIST

- Akdemir, B., Bilgili, E., Ziarati, M., Stockton, D. (2008). *Supply and demand in shipping market using intelligent neural networks*. International Maritime Lecturers Association 16th Conference on MET, Izmir, Turkey.
- Devic, J. *Weighted Moving Averages: The Basics*. Retrieved July 20, 2012 from <http://www.investopedia.com/articles/technical/060401.asp#axzz25dIkTM00>
- Moon, S.H. (2011). *SPM 232: Port Management unpublished handout*. World Maritime University, Malmö, Sweden.
- Barros, C., Haralambides, H., Hussain, M & Peypoch, N. (2011). *Seaport efficiency and productivity growth*. International Handbook of Maritime Economics (2011). (pp 363-382). Edward Elgar, Cheltenham, UK.
- Beenstock, M. & Vergottis, A. (1993). *Econometric modeling of world shipping*. London: Chapman & Hall
- Bergantino, A.S. & Musso, E. (2011). *A multiple-step approach to model the relative efficiency of European ports: the role of regulation and other non-discretionary factors*. International Handbook of Maritime Economics (2011). (pp 383-404). Edward Elgar, Cheltenham, UK.
- Bibby Ship Management & Dehutech, *Guideline for lay-up of ships*. Retrieved July 20, 2012 from <http://www.gac.com/upload/GAC2010/Brochures/Solutions/Ship%20Lay%20Up%20Guidelines%20Mar10.pdf>

Buhmann, M. D. (2003). *Radial Basis Functions : Theory and Implementations*. (pp 209-230) Cambridge University Press, West Nyack, NY, USA.

Cariou, P. and Notteboom, T. (2011). *Bunker costs in container liner shipping: are slow steaming practices reflected in maritime fuel surcharges?* Current Issues in Shipping, Ports and Logistics. (pp 69-82). Uitgeverij UPA University press Antwerp, Belgium

Certin, C.K. & Cerit, G. (2010). *Organisational effectiveness in seaports: a system approach*. International Handbook of Maritime Business (2010). (pp 174-197). Edward Elgar, Cheltenham, UK.

Chau, Foo-tim Gao, Junbin Liang, Yi-zeng (2004). *Chemical Analysis, Volume 164 : Chemometrics : From Basics to Wavelet Transform*. (pp 1-22, 99-147). Wiley-Interscience, Hoboken, NJ, USA.

Cooper, W. W. Seiford, L. M. Zhu, J. (2004). *Handbook on Data Envelopment Analysis*. (pp 1-22, 41-49). Kluwer Academic Publishers, Hingham, MA, USA.

Cullinane, K.P.B. & Wang, T.F. (2006). *The efficiency of European container ports: A cross-sectional data envelopment analysis*, International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management, 9:1, 19-31"

de Koster, M.B.M., Balk, B.M., van Nus, W. (2008). *The applicability of data envelopment analysis to benchmarking of container terminals*. Retrieved July 20, 2012 from <http://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=4&cad=rja&ved=0CDwQFjAD&url=http%3A%2F%2Fwww.mhia.org%2Fdownloads>

[%2Findustrygroups%2Ficmhe%2Fcolloquium%2F2008%2Fde%2520Koster.p
df&ei=gxGUML6E8Hh4QSptoC4Bg&usg=AFQjCNEBgB8G8WgtUaXGVi
MDHBHxi442RA](#)

Drewry Shipping Consultant (1999-2012). *The Drewry Monthly*. Drewry Shipping Consultants Limited, London, UK.

DTREG. *RBF Neural Network*. Retrieved July 20, 2012 from
<http://www.dtreg.com/rbf.htm>

Duc, T.L. (2005). *Forecasting dry bulk freight market*. World Maritime University, Malmö, Sweden.

EEO. *The shipping market in the first half year: Index below 1000 point, competition of loss (Chinese Version)*. Retrieved July 20, 2012 from
<http://www.eeo.com.cn/2012/0710/229663.shtml>

Erdem, S. & Kocakoc, I.D. (2010). *A new ANN training approach for efficiency evaluation*, Hacettepe Journal of Mathematics and Statistics, Volume 39(3) (2010), 439-447.

ESA. *Neural Network Glossary. Earth Home 4.2.5*. European Space Agency. Retrieved July 20, 2012 from
<http://envisat.esa.int/handbooks/meris/CNTR4-2-5.htm>

Fayyad, U., Piatetsky-Shapiro, G., & Symyth, P. (1996). *From Data Mining to Knowledge Discovery in Databases*. Retrieved July 20, 2012 from
<http://www.kdnuggets.com/gpspubs/aimag-kdd-overview-1996-Fayyad.pdf>

Fine, T. L. Lauritzen, S. L., Lawless, J. (1999). *Feedforward Neural Network*. (pp 144-161). Methodology. Springer, Secaucus, NJ, USA.

Global Security. *Container ship types*. Retrieved July 20, 2012 from <http://www.globalsecurity.org/military/systems/ship/container-types.htm>

Graupe, D. (2007). *Principles of Artificial Neural Networks (2nd Edition)*. World Scientific, River Edge, NJ, USA.

Hansen, J.V.* and Nelson, R.D. (2003). *Forecasting and recombining time-series components by using neural networks*. Journal of the Operational Research Society (2003) 54, 307-317

Hu J.S., Xiao D.R., & Xia J.M. (2005). *Analysis of forecasting economy based on the wavelet neural network*. Nanjing University of Information Science and Technology, Nanjing, China.

International Maritime Organization, *The development of the Hong Kong Convention*. Retrieved July 20, 2012 from <http://www.imo.org/ourwork/environment/shiprecycling/pages/Default.aspx>
ISL, *Shipping Statistics Yearbook (from 1997 to 2012)*. Institute of Shipping Economics and Logistics, Bremen, Germany.

Jiang, P.F., Cai, Z.H. (2006). *Combined algorithms for training RBF neural networks based on genetic algorithms and gradient descent*. Journal of Computer Applications 2007, 27(2) 366-368

Lloyd's List (1993-2012). *Lloyd's Shipping Economist Monthly*. Lloyd's List, London, UK

- Lyrids, D.V., Zacharioudakis, P., Mitrou, P., & Mylonas, A. (2004). *Forecasting Tanker market using Artificial neural networks*. National Technical University of Athens, Athens, Greece.
- Ma, S. (2011). *Maritime Economics*. Unpublished lecture handout, World Maritime University, Malmö, Sweden.
- MATLAB, *Wavelet Families*, Matlab Product Documentation. Retrieved July 20, 2012 from <http://www.mathworks.se/help/toolbox/wavelet/ug/f8-24282.html>
- NIST. *Box-Jenkins models*. *Engineering Statistics Handbook* 6.4.4.5. Retrieved July 20, 2012 from <http://www.itl.nist.gov/div898/handbook/pmc/section4/pmc445.htm>
- NIST. *Introduction to Time Series Analysis*. *Engineering Statistics Handbook*. 6.4. Retrieved July 20, 2012 from <http://www.itl.nist.gov/div898/handbook/pmc/section4/pmc4.htm>
- Niu D.X., and Xing M. (1999), *A Study on Wavelet Neural Network Prediction Model of Time Series*, *Systems Engineering-theory & Practice*, (1999) 5
- Notteboom T. (2006). *The time factor in liner shipping service*. *Maritime economics & logistics*, 8:1, (pp 19-39)
- Panayides, P. & Lambertides, N. (2011). *Fundamental analysis and relative efficiency of maritime firms: dry bulk vs tanker firms*. *International Handbook of Maritime Economics* (2011). (pp 85-106). Edward Elgar, Cheltenham, UK.

Shipping Information, *The price of new building ship fell to lowest in the past 8 years, experts say in the next three years, 50% of the ship enterprises will go bankruptcy (Chinese Version)*. Retrieved July 20, 2012 from <http://ship.csi.com.cn/face/hyzxNews/20120702092706.html>

Steenken, D., Vob, S., Stahlbock, R. (2005). *Container terminal operation and operations research - a classification and literature review*. Container Terminals and Automated Transport Systems. (pp 3-50). Springer, Berlin, Germany.

Stopford, M. (2009). *Maritime Economics*, 3rd edition. London: Routledge.

Tao C. (2011). *Quay efficiency of container terminals: Comparison between ports in China and its neighboring ports*. Current Issues in shipping, ports and logistics. (pp 299-314). Uitgeverji UPA University press Antwerp, Belgium

The Baltic Exchange, *Baltic Dry Index*. Retrieved July 20, 2012 from <http://www.balticexchange.com/>

United Sates Census Bureau. *Monthly & Annual Retail Trade*. Retrieved July 20, 2012 from <http://www.census.gov/retail/>

Veenstra, A.W. (1999). *Quantitative Analysis of Shipping Markets*. Delft: Delft University Press.

Visvikis, I. (2011). *SPM 230: Quantitative Methods and Market Analysis unpublished handout*. World Maritime University, Malm ö, Sweden.

Voudris, A.V. (2006). *Analysis and forecast of the capesize bulk carriers shipping*

market using artificial neural networks. Massachusetts Institute of Technology, USA.

Wang, D. (2009). *Analysis of volume of vessel traffic based on BP neural network*. Wuhan University of Technology, Wuhan, China

Wei, H. (2006). *The application of economic cybernetics to forecast in dry bulk market*. Dalian Maritime University, Dalian, China

Wikipedia. *Artificial Neural Network*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Artificial_neural_network

Wikipedia. *Fourier Transformation*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Fourier_transform

Wikipedia. *Gradient descent*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Gradient_descent

Wikipedia. *Haar Wavelet*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Haar_wavelet

Wikipedia. *Maersk Triple-E Class*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Maersk_Triple_E_class

Wikipedia. *Radial basis function network*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Radial_basis_function_network

Wikipedia. *Regression Analysis*. Retrieved July 20, 2012 from http://en.wikipedia.org/wiki/Regression_analysis

Wikipedia. *Wavelet Transformation*. Retrieved July 20, 2012 from
http://en.wikipedia.org/wiki/Wavelet_transform

APPENDEIX: A

The common used wavelet functions

As we mentioned before, the wavelet function is flexible, people can create their wavelet function according to their goal as long as these function follows the characteristic of wavelet.

- Haar

The Haar wavelet is also the simplest possible wavelet, proposed in 1909 by Alfréd Haar. The problem is that it is not continuous and therefore not differentiable because the function contains several quantum transitions.

The Haar wavelet's mother wavelet function can be described as

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 1/2, \\ -1 & 1/2 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

The father wavelet:

$$\phi(t) = \begin{cases} 1 & 0 \leq t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

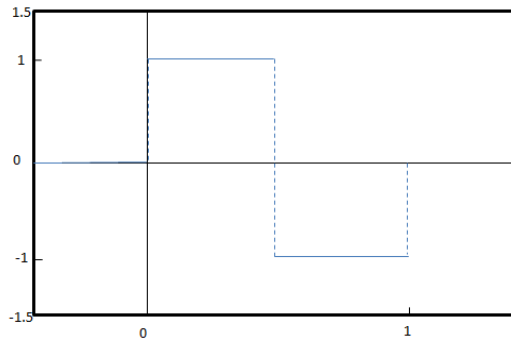


Figure Illustration of Haar wavelet

- Daubechies wavelet

Named after Ingrid Daubechies, the Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support.

Except db1(it`s actually haar), other dbN have no clear expression.

It has several characters:

If $P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k$, then

$$|m_0(\omega)|^2 = (\cos^2 \frac{\omega}{2})^N \cdot P(\sin^2 \frac{\omega}{2})$$

Where $m_0(\omega) = \frac{1}{\sqrt{2}} \sum_{k=0}^{2N-1} h_k e^{-jk\omega}$

Effective supporting length of the wavelet function and scaling function is $2N-1$, and the wavelet function vanishing moments is N .

Most of dbN don't have symmetry, but they are all orthogonal.

The regularity will increase due to the rise of series Number N .

- Symlets wavelet

The $symN$ wavelets are also known as Daubechies' least-asymmetric wavelets. The symlets are more symmetric than the extremal phase wavelets. In $symN$, N is the number of vanishing moments. These filters are also referred to in the literature by the number of filter taps, which is $2N$.

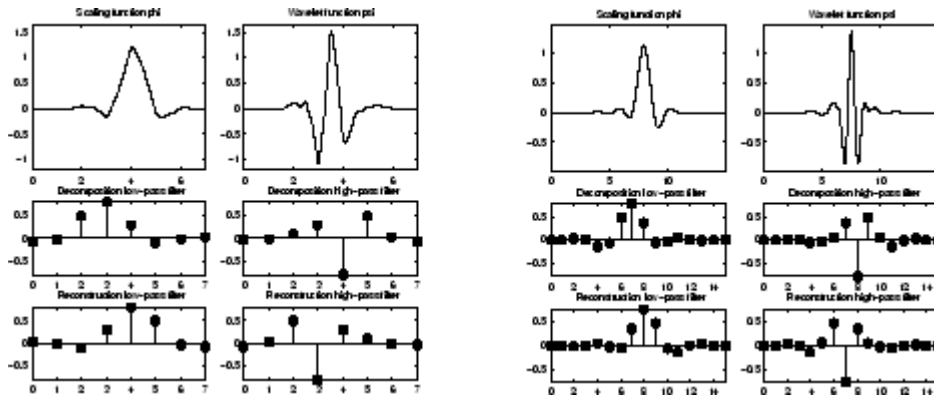


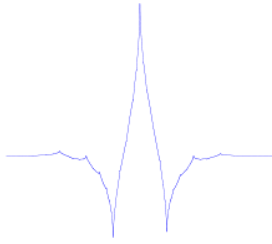
Figure Illustration of Sym wavelet

Source: Matlab Product Documentation,

<http://www.mathworks.se/help/toolbox/wavelet/ug/f8-24282.html>

- Coiflet wavelet

Coiflets are discrete wavelets designed by Ingrid Daubechies, at the request of Ronald Coifman, to have scaling functions with vanishing moments. The wavelet is near symmetric; their wavelet functions have $N/3$ vanishing moments and scaling



functions $N/3 - 1$, and has been used in many applications using Calderón-Zygmund Operators.

Figure Illustration of Coiflet wavelet

Source: DaBler, Coiflet, Wikipedia, <http://en.wikipedia.org/wiki/Coiflet>

- Biorthogonal Wavelet Pairs

The Haar wavelet is the only orthogonal wavelet with linear phase. You can design biorthogonal wavelets with linear phase. Biorthogonal wavelets feature a pair of scaling functions and associated scaling filters — one for analysis and one for synthesis. There is also a pair of wavelets and associated wavelet filters — one for analysis and one for synthesis.

- Mexican Hat Wavelet

This wavelet is proportional to the second derivative function of the Gaussian probability density function. The wavelet is a special case of a larger family of derivative of Gaussian (DOG) wavelets.

The mother wavelet:

$$\psi(x) = \frac{2}{\sqrt{3}} \pi^{-\frac{1}{4}} (1 - x^2) e^{-\frac{x^2}{2}}$$

It is the second derivative of Gaussian function.

There is no scaling function associated with this wavelet.

The analysis and synthesis wavelets can have different numbers of vanishing moments and regularity properties. You can use the wavelet with the greater number of vanishing moments for analysis resulting in a sparse representation, while you use the smoother wavelet for reconstruction.

We can find 7 wavelets in MATLAB software, and we will test the performance one by one, finally get the most suitable one.