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Prediction of Baltic Dry Index by Applications of Long Short-Term Memory Recurrent Neural Network Architectures

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Approval Sheet

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요 약

세계 경기와 마찬가지로 해운경기 역시 그 등락을 반복한다. 2008년 세계 금융위기 이후로 지속적인 경기 침체 및 물동량 감소, 그리고 선박 과잉공급 등의 요소들로 인해 장기 해운 불황이 지속되고 있는 실정이다. 2018년 후반기에는 일부 반등하여 회복되는 추세를 보이나 이가 확실한 해운경기 회복의 신호일지는 미지수이다. 이와 같은 장기 해운 불황에 따른 불확실성이 증폭되고 있는 상황에서는 경기추세에 대한 이해뿐만 아니라 예측 또한 그 중요성이 대두되고 있다.

해운경기를 반영하는 지표는 여러 가지가 있으나 그중에서도 건화물운임지수인 Baltic Dry Index(BDI)가 주목받고 있다. BDI는 각종 산업 발전에 사용되는 원자재들을 주요 운송화물로 삼는 건화물 운송시장을 대표하는 지수이다. 해당 지수는 건화물 운송시장의 주요 항로들에서 발생하는 정기용선 계약의 운임률을 기초로 하여 일별 단위로 발표된다. 해운 산업은 전 세계

를 시장의 대상으로 삼는다. 특히, 건화물 운송시장의 운송 대상이 되는 화물의 특성상 BDI는 세계 경기를 민감하게 반영할 뿐만 아니라 세계 건화물 수요의 특성 역시 반영한다. 이에 따라 BDI는 계절성 및 순환성을 강하게 띄어 해당 시계열의 변동성은 매우 높은 것으로 알려져 있다.

본 논문에서는 최근 특정 복잡한 문제에 대한 방법론으로 각광받고 있는 인공신경망을 적용하여 BDI 예측을 연구하였다. 본 논문의 선행연구 결과, 주로 인공신경망 중 다층 퍼셉트론(Multi-Layer Perceptron; MLP)을 활용하여 통계적 기법 등을 결합한 접근법으로 BDI에 대한 예측 성능을 향상시키고자 한 논문들이 대부분이었다. 해당 연구들은 기존의 시계열 예측 기법들과 인공신경망을 결합한 접근법으로 뛰어난 예측 성능을 보여주는 방법론을 제시하였지만, 이는 해당 시계열의 과거의 값들 또는 추세들이 미래에도 반영되어 특정한 형태로 나타나게 될 것이라는 시계열 예측의 대전제를 적극 수용하지 못한 접근법들이라 할 수 있다. 본 논문에서는 이를 적극 수용코자 기존 선행연구들과는 차별되는 접근법으로 순환 (구조) 신경망(Recurrent Neural Network; RNN)과 기존 순환 신경망의 한계점인 기울기 소실 또는 발산 문제(vanishing or exploding gradient problem)를 극복한 장·단기 메모리 순환 신경망(Long Short-Term Memory; LSTM)을 BDI 시계열 예측에 적용하였다. 추가적으로 전통적 시계열 예측방법론인 아리마 (Auto-Regressive Integrated Moving Average; ARIMA) 모델 중, 비계절성(non-seasonal) 단변량(uni-variate; BDI) 아리마를 통해 단기 예측을 수행하였다. 그 결과로 단기 예측에도 불구하고 아리마 시계열 예측의 정확도는 매우 떨어지는 것으로 나타났다. BDI 시계열의 특성상 계절성 아리마, 다변량 아리마 모형과 같은 보다 세밀한 방법론들의 적용을 통한 예측 성능 향상의 가능성이 매우 높다. 그럼에도 불구하고 본 논문에서 적용된 아리마 모형은 통계학 기반의 방법론과 인공 신경망 기반의 방법론들 간의 단순한 예측 성능 비교의 대상으로써 한정 지었다.

연구의 대상이 된 기간은 2009.04.01.부터 2017.07.31.까지이다. 인공 신

경망들을 통한 BDI 시계열을 예측을 위해 해운경기 및 운임과 관련된 8개의 시계열 자료들을 투입 변수로 설정하였다. 인공 신경망을 활용한 예측은 두 단계로 나누어 진행하였다. 첫 번째로 해당 시계열에 대한 인공 신경망들의 적용 가능성을 파악하기 위해 학습과 테스트 데이터 셋으로 해당 데이터를 나누어 학습 데이터만을 통해 학습을 진행 후 테스트 셋에 대한 적합도를 확인하였다. 두 번째로 이동 시계열 분석 기법(sliding-window method)을 적용하여 $(t+n)$시점의 출력 변수 $y_{(t+n)}$의 값이 $(t+n-1)$시점의 $x_{(t+n-1)}$의 값들에 의해 발생한 것으로 가정하고 해당 인공 신경망들을 학습시켜 1 년의 기간(2016.08.01. ~ 2017.07.31.)을 대상으로 일일 예측을 진행하였다. 해당 단계에서는 첫 번째 단계와 동일한 네트워크 구조를 사용하여 시계열의 다른 시간범위 또는 미래시점에서 해당 네트워크들의 성능의 우수성을 증명하였다. 그 결과로 장·단기 메모리 순환 신경망, 순환 신경망, 다층 퍼셉트론의 수순으로 BDI 시계열에 대한 뛰어난 예측 성능을 보여주었다.

본 연구에서는 적용된 인공 신경망들의 BDI 시계열 단기 예측에 대한 우수성을 증명함과 동시에 장·단기 메모리 순환 신경망을 특정 시계열(BDI)에 적용한 최초의 연구에 그 의의가 있다. 하지만 해당 인공 신경망들은 동일한 설정 값으로 미래의 시점 또는 예측 대상이 되는 기간 등이 달라질 경우 그 예측 성능을 항상 보장할 수 없다. 이는 다른 시계열 자료에 대해서도 마찬가지일 것이다. 따라서 보다 정밀한 선행연구 및 투입 변수들의 선정 또는 다양한 방법론들의 적용 및 응용을 통해 해당 인공 신경망 모델들의 BDI에 대한 예측 성능 향상 및 장기 예측에 대한 적용 가능성을 기대할 수 있다. 해당 주제에 대한 추가적인 연구는 불확실성이 뚜렷한 현 세계경제 상황에서 건전한 해운기업 경영을 위해 보다 과학적이고 합리적인 의사결정을 위한 보조지표로써의 역할을 할 수 있다.

핵심어: *건화물 운임지수; 시계열 예측; 인공 신경망; 순환 신경망; 장·단기 메모리 순환 신경망.*

Prediction of Baltic Dry Index by Applications of Long Short-Term Memory Recurrent Neural Network Architectures

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Abstract

As like the global economy, the maritime economy repeats its fluctuations. Since the global financial crisis in 2008, the ongoing recession and decline in freight volume and oversupply of vessels have led to a long-term recession in maritime economy. In the latter half of 2018, it is recovering and rebounding, but it is not clear whether this is a sign of recovery in the maritime economy. In the situation where uncertainty is growing due to the long-term shipping recession, not only the understanding of the economic trend but also the importance of forecasting is also rising.

Baltic Dry Index (BDI), which is an indicator of the dry cargo freight rate, is attracting attention. It is an index representing the dry bulk shipping market, where raw-materials used for various industrial developments are regarded as major freight. The index is announced on a daily basis based on the freight

rates of the time-charter contracts occurring on the major routes of the dry bulk shipping market. The shipping industry makes the world as the target market. In particular, due to the nature of freight to be transported in the dry bulk shipping market, BDI not only reflects the global economy sensitively but also reflects the characteristics of global demand for dry bulk. As a result, BDI is highly seasonal and cyclical, and the volatility of the time-series is known to be very high.

This thesis focuses on BDI prediction by applying Artificial Neural Network (ANN), which is popular as a methodology for specific complex problems. As a result of the literature reviews, most of the papers have been used to improve the prediction performance of BDI by utilizing various statistical techniques with combinations of ANN models, especially, MLP (Multi-Layer Perceptron) was used. These studies suggest a methodology that shows excellent predictive performance by combining or manipulating existing time-series prediction techniques with ANN. However, the basic premise of time-series prediction that the past values or trends of the relevant time-series will be reflected in the future, was not taken into consideration. In this thesis, unlikely to other studies of related fields, another method named Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) were applied to BDI time-series prediction. Especially, LSTM is the special application of RNN that made to overcome the 'vanishing or exploding gradient problem' of RNN. In addition, a short-term prediction was performed through a traditional time-series prediction methodology named Auto-Regressive Integrated Moving Average (ARIMA) model. Non-seasonal uni-variate ARIMA model was conducted in the research. As a result, despite the short-term prediction, the accuracy of the model prediction is very poor. Due to the nature of BDI time-series, there is a high possibility of improving prediction performance by applying more detailed methodologies such as seasonal and/or multi-variate ARIMA models. Nevertheless, the ARIMA model applied in this paper is limited to simply only for predictive performance comparisons between statistical-based methodologies and ANN-based methodologies.

The period of study was from April 1, 2009, to July 31, 2017. To predict BDI time-series through ANN. Eight independent time-series that related to shipping and freight rates were set as input variables. ANN predictions will be split into two phases. First, in order to grasp the applicability of ANN to the given time-series datasets, divided the time-series data into training and test datasets, followed by learning through only the training datasets, and then confirmed the fitness for the test set. Second, a sliding-window method was applied. The time-series datasets are intentionally put back 1-day. Therefore, ANN models are trained on the premise of the output variable of $y_{(t+n)}$ at $(t+n)$ is occurred based on the input variables of $x_{(t+n-1)}$ at $(t+n-1)$. After that, a daily prediction is conducted for a 1-year (from August 1, 2016, to July 31, 2017). In this phase, to demonstrate the superiority of the performance of the networks over different or future time windows in the given time-series, using the same network structure as the first phase. As a result, LSTM showed the most well performed predictive performance while the second and the last were RNN and MLP, respectively.

Contributions of the thesis are that it showed the superiority of ANN for short-term prediction of BDI time-series and it is the first study of applying LSTM to the specific time-series (BDI). However, the studied ANN models cannot always guarantee the same or similar prediction performance when in the future time point or changes in the prediction object period. This phenomenon also might arise in other time-series datasets. Therefore, it is expected that the prediction performance of BDI of corresponding ANN models can be improved through more precise literature reviews and selection of input variables or application of various methodologies. Even the applicability of long-term forecasting can also be sought. Further research on the subject could serve as a supporting indicator for more scientific and rational decision-making for sound shipping business management with the current global economic environment where uncertainty is evident.

KEY WORDS: *Baltic Dry Index (BDI); time-series prediction; Artificial Neural Network (ANN); Recurrent Neural Network (RNN); Long Short-Term Memory (LSTM).*

Chapter 1 Introduction

1.1. Research Background

After the financial crisis of 2008, the chain effect of the crisis has spread out to the whole world. Especially Greece exceedingly suffers from it even though they have partially repaid the debt by relief loan, but still persisting with remaining obstacles now in 2017. Moreover, China which is one of the fastest emerging countries in East-Asia, in the aspect of the economy which might be regarded as one of the solutions for global economic depression. However, after the dissemination of the effect in 2012, China gradually ceases the aggressive pump-priming and consequently, deepening of depression is now undergoing. India is referred to as the other newly emerging nation. India's prospects of economic-related indices are showing an increasing trend. However, only with prospects might be limited in contribution to the regional recovery and which is not the certain evidence to that the economic growth of India will provide for vitality to the world economy.

The chain effect of the crisis also hugely influenced world trade. According to International Chamber of Shipping (ICS), around 90% of world trade is carried through seaborne trade, which means that world shipping economy that includes both the liner and the tramp shipping market can be directly affected by excessive negative feedback of the financial crisis. A representative example of economic difficulties in the shipping business, the company Hanjin Shipping in Korea, bankrupt in early 2017, mainly caused by irrational and imprudent investment conducted without taking into account market cyclicity. Another instance of the shipping crisis influenced by the economic chain effect is the reorganizations of shipping alliances in the liner shipping market. The fundamental reason of this phenomena is to fully utilize their vessels while reducing operating costs in order to achieve economy of scale. It can be explained as a provisional strategy against to tackle operational difficulty under the economic depression. These patterns also can be seen in the tramp shipping market as the growth in the number of bulk shipping pools have the same purpose as liner shipping players. Furthermore, many other figures show recession, especially in the dry bulk industry. Bankruptcy filings peaked in 2015, and the percentage of companies reporting negative EBITDA[1] reached more than 60. In particular, the Baltic Dry Index (BDI) that represents the current state of affairs of the dry bulk shipping market decreased steeply after the crisis. It revealed more volatile and hit the lowest point of 290 ever in February 2016.

1) EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization)

In the manner of dealing with the shipping market uncertainty, rigorous studies on forthcoming trends are needed. Especially, in the dry bulk shipping market, BDI is receiving attention from both practitioners including shippers and investors. Also, academics within related disciplines are showing interest since the index has gained more spotlight than before. There are several approaches that deal with future events in the dry bulk shipping market, such as investors' or professionals' view of market prospects, studies of micro or macroeconomics, trading Forward Freight Agreement (FFA) to hedge market risks and may even intuition of market speculators. However, under the conditions of the global economy, maritime business is also depressed and, notably, more prolonged recession is undergoing, especially in the dry bulk shipping market. Furthermore, trough trends still continued in 2018 and no one can simply predict future outlooks, even someone concerned with pessimistic perspectives. Consequently, to succeed in the dry bulk shipping market, in the aspect of risk management of the shipping business while other risks exist, both 'business risk' and 'market risk' should be examined as a top-priority tasks due to the previously discussed volatility and complexity of the tramp shipping market ecology and the world economic status. Therefore, a scientific and quantitative perspective of decision making should be implemented. Moreover, it is most likely that people of related fields of academical studies and business practices who have a desire of implementing diverse methodological-tool-kits will increase while elimination of any human bias for relatively superior investments.

1.2. Research Purpose

In order to achieve the aforestated challenges, prediction of the future directions of the market should be conducted in advance with perceptive and precise understanding of the dry bulk shipping market and employ most of the related factors as much as possible that are likely to have an effect on BDI. In this thesis, to predict the future value of BDI, applying popular machine learning algorithms or techniques that are termed Artificial Neural Network (ANN). BDI is time-dependent, so it is necessary to choose a specific architecture from diverse tribes of ANN that have a memorization term (can store patterns or features of past values of time-series) in hidden nodes which are termed Long Short-Term Memory (LSTM) that fall under the category of Recurrent Neural Network (RNN), rather than exploit Single or Multi-Layer Perceptron (MLP). Further discussion on the reason for choosing LSTM will be held later, along with a comparison with the conventional statistical methods. To the best of the author's knowledge, this is the very first time predicting BDI time-series using LSTM.

Objectives of the thesis can be defined as follows: Firstly, to design an outperformed ANN architecture in order to build an application for BDI time-series prediction that consider past values with time-dependency through LSTM. As a result, in substance, it can also be an approval of applicability of LSTM to BDI time-series. Secondly, to compare the performances of the predictions made by various models to propose robustness of LSTM as a predictor for BDI time-series. Consequently, it can also be used for decision making with rationality even under the uncertain and complex world economic conditions.

1.3. Research Scope

As aforestated, the scope of the thesis will only concern the dry bulk market. Note that complex dynamics of the market in the maritime business are affected by each other dependently.

One of the successful conventional statistical models is the Auto-Regressive Integrated Moving Average (ARIMA). It is renowned in both statistics and econometrics, and in particular, in time-series prediction. In this thesis, the standard non-seasonal ARIMA model invented by 'Box-Jenkins' will be applied to predict 30-days only in given periods of BDI time-series. It only makes a prediction with non-seasonal uni-variate data (BDI time-series).[2)] The purposes for implementing the model are defined as follows:

- Forecasting BDI time-series with the one of popular conventional statistics tools.

- Emphasizing outstanding performances of ANN architectures by comparing with the results from the standard ARIMA model.

2) The thesis is to compare the models performances only, not the fundamental academical or mathematical studies between the statistical model and various ANN architectures. ARIMA model will be implemented with one x variable (BDI time-series) as a non-seasonal uni-variate ARIMA model, while ANN architectures with multiple x variables.

ANN architecture was inspired by biological neural networks of the human-brain. It is counted as one of the successful frameworks or applications to solve many complex problems. The model requires data-intensity to generalize learnt patterns using given datasets. It means the more data points of time-series fed to the networks will likely to generalize the prediction results for unseen datasets better. Similar to the purpose of utilizing the ARIMA model, a certain model of ANN called MLP was used. It consists of, at least, three layers: Input, hidden, and output layers with arbitrary activation functions. It is useful in applications to solve extremely complex problems. Even, it does not require any pre-assumptions appearing in the field of statistics. Also, it has been proven by many researchers and practitioners that it has often performed better than any other models.

Recurrent architectures of ANN were also utilized. Two models were used: Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). There are two different applications in RNN architecture: 'Elman network' and 'Jordan network'. The Elman application was used in this thesis. The distinction between the models came from existence of 'context unit'. It will be addressed in a later chapter. Base principals of RNN are the same as MLP. It has a multi-layer but the fundamental framework is recursive architecture as seen from the name of it. The key application of the thesis is LSTM. It is an improved model of RNN that overcame the 'vanishing or exploding gradient problem' by adding 'hidden state' and 'cell state' to the network. Each state of cells is able to memorize relatively long periods of weights of past and current cells well. Then it is used in 'weights update rules' of current input and then pass them to the future cells recursively. It allows the network to have a more powerful memorization capacity. Therefore, the network is known to be well suited for predicting sequential or time-series data.

All of the ANN models of applications will perform in multi-variate predictions that feed 8 variables as inputs for training and fitting to the 1 variable (BDI) defined as a 'many to one' prediction problem. The time-series data used are maritime business related, especially that are likely to influence BDI. Training and prediction step will be conducted into two phases. The first is to verify the 'goodness of fitness' of ANN models to BDI time-series with the others time-series that feed to networks as input variables. The second phase will be daily forecasting with the sliding-window method. Only 1-day ahead forecasting will be conducted for a 1-year (from August 1, 2016, to July 31, 2017). The proposed structures of ANN models through the phase one will be imported as like a part of backtesting strategy. That to confirm the prediction ability of the networks with different time windows are able to sustain its predictability in the future time windows.

1.4. Research Procedure

For a successful prediction of BDI, the introduction began with addressing the current state of affairs in maritime business, especially the dry bulk shipping market that along with world economic depression.

Before digging into the main topic, the scope of the thesis will be limited to the dry bulk shipping market which is the sub-sector of the tramp shipping. The prediction objective is BDI which is a composition of indices of typical types and voyage routes of vessels in the dry bulk shipping market that transport dry bulk cargoes all over the world.

Next, general characteristics of the shipping market will be summarized. A certain intersection exists that has a linkage with the dry bulk shipping market. Also, the characteristics of both the dry bulk shipping market and BDI will be explained to clarify relationships between them. The main characteristics of the dry bulk shipping market will be defined as cyclicity, seasonality, and volatility that were derived from the literature reviews. Consequently, the index BDI is very intimately connected with the dry bulk shipping market and depends on its market characteristics. According to the literature reviews, there were evidence of BDI's role as the world economic leading indicator or barometer.

After that, literature reviews will be conducted. It will only focus on BDI prediction researches even though there are others of shipping market indices predictions. It is mainly categorized into two sectors. One is statistics-based, and the other is ANN-based prediction. Then, findings and limitations from the literature reviews will be drawn.

Brief descriptions of formulas and algorithms of models will be described. Simple explanations of the sliding-window method for daily forecasting of 1-year period will follow up and also basic assumptions. Next will be a descriptive summary of datasets, research environments, and lastly summarized structures of designed ANN architectures.

Later, will be the results of the experiments. As described in the research scope, results of prediction of non-seasonal uni-variate ARIMA model will be solely depicted only in short-term periods to show forecasting capabilities of its own. Then two-phases of experiments for forecasting through ANN architectures will be described. Firstly, identifying and comparing 'goodness of fitness' for trained ANN architectures will be provided. Secondly, the daily forecasting of 1-year period will be conducted through each of the models by applying the sliding-window method. Finally, the forecasting errors will be calculated and compared.

At last, conclusions with the significance of the thesis, limitations, and possible future studies will be drawn.

1.5. Research Structure

Chapter 1 described the background and purposes of the thesis. The scope of the research that deals with the dry bulk shipping market consist of five major bulks. Chapter 2 will describe the dry bulk shipping market and BDI in aspects of microeconomics (supply and demand). Next, chapter 3 will minutely study the literature of related topics that predict BDI with statistical-based approaches especially ARIMA model, and ANN-based approaches. After that limitations and findings will be derived. Chapter 4 will demonstrate the principles of each methodologies, basic assumptions, and how they are applied in the thesis with the descriptions of time-series. Non-seasonal uni-variate ARIMA model will be employed that only uses one variable (BDI) to predict short periods of 30 days. Again, only restricted prediction results comparison will be carried out. Prediction of BDI time-series with ANN models will be conducted in two phases. The first phase identifies fitness of neural network with general train-test (7:3) split. And the second phase will use the sliding-window method for daily prediction for a 1-year period of BDI time-series. Note that all the datasets used will be pre-processed and described in this section. Chapter 5 will illustrate prediction results. Lastly, contributions and conclusions with limitations of research will be drawn in chapter 6.

Chapter 2 The Dry Bulk Shipping Market and Relations with Baltic Dry Index

BDI has the main role of an economic leading indicator, but fundamentally, it represents the status of the dry bulk shipping market. This chapter will define the scope of the dry bulk shipping market, and describe the nature of it.

2.1. Define the Tramp Shipping and the Dry Bulk Shipping Market

Most major services or products of the merchant shipping industry are transportation services. It can be divided into several specific types of markets which depend on the characteristics or types of the cargoes. After the globalization, segmentation of the shipping industry has become more unified and specialized. It was formed and classified as the liner shipping market and the tramp shipping market that carried general cargoes (finished or semi-finished manufactured goods) and bulk cargoes (coal, grain, iron ore, petroleum products, etc.) respectively. The tramp shipping market is characterized as 'intermittency of market demands' that differ from the liner shipping market. It does not have fixed schedules nor published ports of call, due to irregularity in demands that only occurred with shippers needs.

After the 1970s, developments in the tramp shipping market arose, and commodities are carried by more specialized tramp shipping markets in the manner of 'one-ship, one-cargo' basis. The trend was increased to achieve economies of scales while reducing both operating costs and average haul. The tramp shipping market appeared more distinguished by the types of carried cargoes. Its four main categories are as follows: The five major bulk (bauxite, coal, grain, iron ores and phosphates), the minor bulk (cement, steel products, sugar, forest products, etc.), the liquid bulk (crude oil, liquid chemicals and petroleum products) and the specialist bulk cargoes (motor vehicles, refrigerated cargoes and special cargoes) which required specific storing and handling. These formations of the market are still maintained nowadays in the tramp shipping market since its developments.

In accordance with the circumstances of the market segment and to focus on the objectives of the thesis to predict BDI time-series, the scope of arguments will only be limited to the dry bulk shipping market, particularly those that belong to the sub-sector of the tramp shipping market. BDI is a composite of time charter average indices of specific types of vessels called Capesize, Panamax, Supramax, and Handysize. Ever since March 1, 2018, Handysize has been excluded from the calculation of BDI. All sub-indices are only corresponding to special types of vessels for the dry bulk cargoes. Therefore, the liquid bulk and the specialist bulk cargoes will not be discussed in the thesis.

2.2. Characteristics of the Dry Bulk Shipping Market

2.2.1. Understanding General Characteristics of the Shipping Business

Before describing the nature of the dry bulk shipping market or its economics in detail, clarification of general characteristics of the shipping business need to be clarified in brief. The nature of the dry bulk shipping market is overlapped and derived from general factors of the shipping business. Note that the general characteristics are not only applicable in the case of the tramp or the dry bulk shipping market, but also in the other remaining shipping market sectors.

The shipping business as a transportation service is transporting commodities or merchandise goods worldwide. From the nature of the business, it is necessary to operate a vessel to transport goods from departure port to destination port. A vessel can transport a large quantity or enormous volume of cargoes in a single iteration that any other modes of transport such as aircraft, rail, truck, pipeline cannot compete against. Even, transportation cost per unit is relatively inexpensive which means that it can easily achieve economies of scales by developing a gigantic vessel under the assumption that technological limitations are solved. Generally, the price of a vessel is expensive, so the shipping business is depicted as a 'capital intensive industry'. The other general characteristic is relatively slower delivering speed than any other modes of transport, and the average distance of travel is lengthy. Lastly, of course, while there are many other industries competing internationally, the shipping business can be considered as the most competitive market in global scale. Basically, the demand of the shipping business occurred globally so the trades made through bill of ladings and their profit will be earned from the quantity of goods transported after deducting both capital and operating expenditures. Also, the origin of the demand came from uneven distribution of natural resources and discordance between where the area of production and consumption. Understandably, it is an essential service for importing and exporting of raw-materials and commodities.

The general characteristics of the shipping business are summarized as follows:

- Shipping can deliver cargoes world-widely anywhere the ocean exists.

- It is an international business. Demand of the shipping business is based on the quantity of goods needed to transport through sea which means that it is highly dependent on the state of global economy.

- Being able to transport a large quantity at once and farther delivery in a cheaper price can easily achieve economies of scale.

- Building and operating vessels requires plenty of capital, so it is regarded as a capital intensive industry.

2.2.2. Seasonality and Cyclicity of the Dry Bulk Shipping Market and Relations with Global Economy

Under the circumstances of the shipping business, especially the tramp shipping market, which primarily aims to transport bulk cargoes is not only considered as highly world economic situation dependent, but can also be susceptible to various factors. Characteristics or behaviors of the tramp shipping market can be interpreted and understood by both researchers and practitioners by applying supply-demand functions. Both supply and demand factors interact constantly to achieve against the equilibrium state of freight rates, but it never reached the point due to various factors. All the time, it is highly volatile. While suppliers' mainly focusing on adjusting their arrangement and operating volume of vessels in the market with retaining low costs as possible to retaining payability, demands of seaborne trades are depend on world economic phenomena that oscillated upwards and downwards, which may seem as random-walk behavior. Reasonably, it also derived from various factors such as the political, the social and the physical environment of nations that are affected by or with it. Major cargoes by trampers are mostly raw-materials and commodities which are combination of both liquid and dry bulks. Demand for stated cargoes has occurred to produce most goods and services consumed worldwide. Therefore, the demand of bulk cargoes is truly related to the economic situation of the whole world. The other distinctive nature of maritime business can be defined by the terms of capital-intensity due to the price of its main assets which mostly consist of vessels. Shipping companies usually procure capital banks or investors. In other words, it has high leverage ratios, but much of the liabilities are likely to be paid back in the future. It may be the root cause for ship owners or market investors to have reckless minds that tempt to speculate in the market with a bias which lead to oversupply vessels in the market that also influence to create market bubbles. In addition, significant intrinsic phenomena of the tramp shipping market can be explained by the theoretical model of 'close-to-perfect market' or 'close-to-perfect competition' while contrasting with the general cargo market. The meaning of close-to-perfect market is that it is nearly impossible for tramp ship owners or investors to earn the profit over the capacity of demands of its market themselves. Such complex schemes of the tramp shipping market economies are darkening prediction of its own market status, even for both economist and old hand practitioners.

The bulk shipping market, which is a sector of the tramp shipping market, is also highly dependent on the global economy. It follows the same characteristics of the tramp shipping market as its business cycles are composed of short-term cycles of seaborne trades, and medium to long term trends are driven by a regional development cycles. Examples of the intrinsic factors in demand are seaborne trades, average haul, transport costs and random shocks that include political issues, war, natural disaster, and so forth. Supply factors are world merchant fleet, shipbuilding deliveries, fleet productivity, scrapping and losses and freight revenue. Also, there are many other extrinsic factors such as second-hand ship price, oil price (bunker fuel oil C) and charter rate. Stopford (2013) defined five affecting variables that are the most likely to affect for the both demand and supply of the shipping market model. It took a place in *Table 1*.[3)]

Table 1 Demand and supply affecting variables for the shipping market

Demand	Supply
The world economy	World fleet
Seaborne commodity trades	Fleet productivity
Average haul	Shipbuilding production
Random shocks	Scrapping and losses
Transport costs	Freight revenue

The interactions between these multiple factors increase the dynamics of BDI that appear as cyclical and seasonality trends in the most exceedingly volatile market. To the best of the author's knowledge, there is no other market that displays similar movements. Stopford (2013) defines the shipping cycles as composition of two major trends: One is a short-term cycle and the other is a long-term cycle (secular trends). In the short-term cycle, the shipping market shows a typical cyclic pattern. It is defined as the mechanism of coordinating supply and demand in the shipping market that assign periodicity to the cycle. The complete short-term cycle is composed of four stages. The composition is as follows.[4)]

- Trough: Low demand and freight rates while exceeding in supply.

3) Stopford, M., 2013, *Maritime Economics*, 3rd edition, Routledge: London, p. 136.
4) Ibid., p. 98. [The context was summarized by the author of this thesis.]

- Recovery: Increase in freight rates and the market is willing to be an equilibrium in supply and demand.

- Peak: The highest point recorded in freight rates. Supply and demand of the shipping market at or near the market equilibrium.

- Collapse: Supply exceeds demand and freight rates are falling.

Stopford (2013) also suggested six of clear sign of through and peak. It can be summarized as follows in *Table 2*.[5)]

Table 2 Definition of trough and peak stages of shipping cycle

Definition of Trough	Definition of Peak
Freight near operating costs	Freight over 3 x OPEX
Old ship prices fall to scrap	5-year-old ship costs same as new building
Litter ordering (usually)	Heavy ordering (usually)
Many demolition sales	Few demolition sales
Banks reluctant to lend	Banks keen to lend
Market sentiment pessimistic	Market sentiment implausibly positive

A detailed descriptions of the nature of the shipping business cycles are omitted. Its purpose is only the introduction for the general knowledges of the shipping cycles that emphasize existence of the cyclicity and seasonality.

Papailias, Thomakos, and Liu (2017) claimed that there are two typical problems that make harden to predict future trends of the shipping business,

5) Ibid., p. 97.

especially, in the dry bulk shipping market sector. It differ from any other markets by these two factors: 'endogeneity' and 'supply lags'. These special endemic characteristics of the market make particular movements and cycles.

- Endogeneity: Cost of shipping affect to, on the contrary, and is affected by global economies at the same time. It means that is difficult to implementing and interpreting its circulus of dynamics with simply using its current economic activity estimates.

- Supply lags: Supply of freight services is derived from four major markets. It is composed of the freight market (derivatives market, voyage market, time-charter market included), the sales and purchase market (second-hand ships), the shipbuilding market (new-build ships), and the demolition market (scrapping old ships). Of course, all the stated markets are related to supplies of vessels and are capital intensive and usually take more than 2 years to build a new ship. Therefore, supply of freight service is very inelastic while demand is not and occurrs worldwide, with the times and spaces being sporadical.

Kavussanos, and Alizadeh-M (2001) investigated seasonality patterns in the dry bulk shipping spot and time charter freight rates. The investigation was examined across different vessel sizes, contract durations, and overall dry bulk market conditions (peaks and troughs). It revealed that there are truly seasonal trends that exist in the dry bulk shipping market and no evidence of its movement being stochastic. Cyclical seasonal patterns exist among the nature and patterns of world trade in commodities transported by ships.

Thorsen (2010) showed studies of the short and long-term relationships between the freight rates in the dry bulk shipping and its business cycles. The study first defined supply and demand of the shipping services and then implemented econometric models with set of time-series that are related with the dry bulk shipping market and other world economic indicators. It revealed that fluctuations of the dry bulk shipping market are intimately caused by factors of supplies and demands which resulted from world economic indicators in short or long-term dependency. Author said that the certain level of changes in the business cycles will affect the market fluctuations that are the results of its own behaviors of progress to market equilibrium. Other research (Scarsi, 2007) also made an assertion of market equilibrium of the bulk shipping business. It is pointed out that the ship owners made wrong decision makings frequently due to ignorance or undervaluation of the market trends or cycles. They only tend to follow their personal intuition and mimic the competitors' strategies, even though, there is certain timing for buying and selling. The author emphasizes the importance of full application of the availing information of markets and scientific analysis should be implemented in practice.

State of affairs of supply in the dry bulk shipping market can be represented by deadweight tonnage (DWT) as market capacity. Referring to report of United Nations Conference on Trade and Development (UNCTAD) in 2016, from 1980 to 2016, percentage share of DWT in the dry bulk carrier kept increasing by 15.91%. It grew by 2.25% during 2015 to 2016, while annual growth of rate in demand (world economy) showed decreasing trends by 2.1% which is lower than the historical average. The growth in supply of the dry bulk shipping market is much lower than the other markets. However, it is not enough to cover the recession in world economics. Average of annual growth of international seaborne trade revealed around 5.6% from 2003 to 2007, while around only 2.9% of average growth was shown after the crisis in 2015. In 2017, percentage share of DWT in dry bulk carrier decreased by 0.3 in comparison to 2016. This was insufficient to cover the recession. During the year, the world economic growth in annual percentage changes only by 2.6. Decrease in the percentage share of DWT does not mean decrease in absolute volume of DWT in the market. Compared to 2016, in 2017, DWT of bulk carriers increased by 17,292 (thousands of DWT) which is 2.22%. In 2018, the percentage of annual change is 2.90 while demand (world economy) only increased to 3.0. It is getting much better as years go by, but still hard to say that the dry bulk shipping market is escaping the trough phase of the shipping market cycle. After early in 2018, several market reports has shown an optimistic view of market prospects, but still no one can easily say that it is truly about to prosper and the market recovery is not temporal. The ambition of the thesis is not focusing on the market prospects. Therefore, the statistical figures only imported for the presentation of recent historical trends of the shipping economics, especially, the dry bulk shipping market. Again the purpose of the thesis is to predict the future value of BDI which driven by the faith in applicability of ANN that it can learn the intrinsic patterns of historical values of given time-series.

Several professional maritime reports in 2018 pointed out major factors of the recession in supply, also current state of affairs of demand and environments of the shipping business are summarized:

Current supply market conditions

- Shipbuilding companies contribute to supply vessels, even despite low-cost orders, as shipbuilding capacity has surged worldwide due to large-scale infrastructure investments made in the up-phase cycle.

- Shipping companies tend to increase in size of vessels to enhance profitability and competitiveness. The cost per unit of transportation decreases as increase in allowable volume of cargoes in one-voyage. The expansion of the Panama Canal has allowed vessels from 5,000 TEU (Twenty-foot Equivalent Unit) originally, nowadays to 14,000 TEU. It has accelerated over-supply in the volume of capacity of vessels.

- Major shipping nations provide various policies in support for their homeland shipping companies. Such policy support makes it difficult for marginal companies to exit the market.

Current demand market conditions

- Global companies pursue global value chain optimization through Supply Chain Management (SCM). This means that the opportunity of transportation allocated to the shipping business may relatively decrease while demand in other mode of transportations increase by the standardization and rationalization in SCM.

- Reshoring is arising by global companies. They move facilities to their homeland for the purpose of protection of international trade and job creation. This will lead to decrease in the quantity of goods transported by shipping.

- Increase in durability of goods and trends of production are becoming 'slim', 'small', and 'light' and are also leading to decrease in the quantity of goods transported by shipping.

Current environments of global shipping business

- Rise in oil price is in progress. Due to the economic downturn, it is hard to reflect an increment of oil price in freight rates.

- Banks are less likely to take risks while uncertainties rampant in the world economy. It leads an aggravation of financial conditions and lack of liquidity to shipping companies.

It is clear that the world market conditions are not good enough to make an economic traction in the shipping business.

2.3. Understanding of Baltic Dry Index

BDI is established by Baltic Exchange in daily basis. It has been revised several times since its first introduction in 1985 as named Baltic Freight Index (BFI).[6] After several decades, it was a composite of the three indices named Baltic Capesize Index (BCI), Baltic Panamax Index (BPI), and Baltic Handymax Index (BHI) since November 1, 1999, and the index renamed to BDI. The index includes both time-charter and voyage-charter average of BCI and only time-charter average for BPI and BCI. They are names of specific fleet classes and normally carry specific dry bulk cargoes with unfixed routes and schedules through the whole world. BDI has been regularly re-examined, after July 1, 2009, is formed with four sub-indices that are named BCI, BPI, Baltic Supramax Index (BSI),[7] Baltic Handysize Index (BHSI).[8] Additionally, after the day, BDI has been comprised solely of the time-charter average of BCI, no longer including the voyage-charter average of it.

Chartering is an important term in the dry bulk shipping market. Demand of the dry bulk shipping occurs by charter party. Time-charter is one form of chartering which engagement between generally ship owner and shipping agent made. Simply, ship owner lend a vessel with the burden of management cost (wages, maintenance, etc.) and fixed cost of shipping (insurance, interests, etc.) as liabilities, while charterer (shipping agent) hire a vessel and pay charterage and operating expenses (port charge, fuel cost, etc.) during the certain periods of times stipulated in the contract. The benefit for the ship owner is that it is able to fully utilize their shipping pools without laying-up vessels and the charterer is able to make a profit with contract of carriage or their own cargoes without taking a risk by

6) Note that, refer to Baltic Exchange, regular re-examination is conducted with annual basis under the base of the fleet composition, total cargo moved-based on import and export, vessel utilization including ballasting, and vessel-tracking data.
7) BSI is a substitution of the sub-index BHI, since January 3, 2006.
8) BHSI was first introduced on January 2, 2007.

possessing their own vessels or shipping pools.

The time-charter average that is used to assessment of BDI is derived from Time-Charter Equivalent (TCE). It is a weighted arithmetic average of TCE for assigned routes with each type of vessel. TCE is formulated on voyage revenues, subtracting voyage expenses and then dividing by the round-trip duration in days. Reference currency is in US Dollar (USD). The formula of TCE is as follows in *Formula 1*.

$$\frac{Voyage\ Revenues\ -\ Voayage\ Expenses}{Round\ Trip\ Duration\ in\ Days} \tag{1}$$

It defines the average daily revenue performance of a vessel. It can be used as chartering opportunities to both ship owners and charterers. Consequently, BDI is a projection of how much the ship owner and charterer fixed rate under the market principles of Supply and demand of shipping economics, especially the dry bulk shipping market in this context. If over-supplied in the market then, the freight rate will get lower, otherwise, too few supplied, it will get higher.

BDI is also known as the leading indicator of world economies. Fluctuations in BDI means the increase or decrease in the number of raw-materials traded worldwide. Changes in the certain level of demands in raw-materials have a close relationship with its supplies, and vice versa. Bakshi, Panayotov, and Skoulakis (2012) found that both growth in global economy activity and BDI has close correlation. The research discovered BDI has predictive ability for typical stocks and even for the returns of commodity indices. It claimed two significant points from elaborate literature reviews.

- "*The BDI growth rate exhibits a positive and statistically significant relation to subsequent global stock returns, commodity returns, and industrial production growth.*"

- "*The predictability is corroborated in statistical terms, ... through metrics of economic significance, and in the presence of some alternative predictors. Movements in the BDI growth rate, thus, capture variation across the real and financial sectors, ...*"

Lin, and Sim (2013) constructed a new measure of trade cost by using the characteristics of BDI to investigate relations between GDP (Gross Domestic Product) and trade in least developed countries. They concluded that 1% of expansion in trade raises GDP per capital by approximately 0.5% on average. Geman, and Smith (2012) proposed diffusion models to present intrinsic features of BDI to interpret its behaviors and relations with world economics. The analysis found that BDI is very volatile up to 60%, than most commodities, stocks, and electricity due to its absence of inventory in supplies. Supply of the shipping business is the shipping services itself, so no inventory to storage. It reacts directly to demands under the premise of surplus of vessels in the market. It concludes with the usefulness of spot price models for the future growth of options on freight rates. Zeng, and Qu (2014) conducted Empirical Mode Decomposition (EDM) to analyse BDI time-series and brake into short-term and long-term trends. It premised that BDI influenced by multiple factors of world economic status. The research concluded that the decomposition method can reveal intrinsic dynamics of bulk freight price and this can lead to decrease in error accumulation of the forecasting. Chistè and Van Vuuren (2014) also claimed cyclical behavior in the shipping market. For the noisy and cyclical patterns of BDI time-series, they used Hodrick-Prescott (HP) filter to denoise daily BDI time-series. Its output is monthly denoised BDI time-series. For extraction of cycle frequencies, Fourier series analysis was used. Its output showed the extracted cycle frequencies with the discarded high frequency signals. Then, they analyzed the final results under the basis of shipping cycles (e.g., trough and peak) by the processed time-series. The research concluded that BDI time-series is a composition of a certain level of iterative variances during some duration. Therefore, good understanding of the shipping cycles lead to prudent investment and decision making rather than using ‘rules of thumb’.

As discussed, the index BDI is the most significant evidence for economical state of the dry bulk shipping market and even can be one of the representative as leading indicator of global economic activity. It measures the demand of raw-materials to global production sites for manufacturing other products while most of world traded raw-materials move through the sea. Other economic indicators such as GDP, consumer expenditures, oil prices, and many others are projections of what have occurred in the past. They can even be distorted or influenced by various factors like policies, trades, speculations. However, the occurrences of demand in the shipping market are only devoted by people who have needed cargoes to move through the sea. While supply is only devoted by those who have reserved cargoes to move through sea with market occupation under the assumption of the certain level of vessels or capacities that are procured in their pools with market competitiveness. Consequently, BDI only takes into consideration both near real-time demands of global raw-materials to be shipped and its reaction of supplies of vessels to voyage. There is no need to argue that the importance of understanding and predicting the future trends of BDI while considering its dynamics.

Chapter 3 Literature Reviews

There were diverse approaches that could be found from prior studies. It can be mainly categorized into two sectors. One is statistics-based, and the other is ANN-based prediction of BDI and sub indices (BCI, BPI, BSI, and BHSI). Findings and limitations of them will be drawn at the end of the chapter. As the thesis is only limited in the research scope, literature reviews only dedicated to the dry bulk shipping related studies will be dealt with. Note that the thesis is the very first approach to predict BDI time-series by using LSTM so it was difficult to find literature of conducting a prediction by RNN architectures. The literature reviews are only limited to summarize various approaches, not for academical motivations in prediction model constructions or to make an improvement in former approaches. Nevertheless, note that it is still valuable to use predefined problems, mixed-strategies, improving conventional methodologies, and so forth, or even develop another level of model construction. In this thesis, all the applied ANN architectures are plain version of them.

3.1. Statistical Based Prediction of Baltic Dry Index

Papailias, Thomakos, and Liu (2017) showed empirical analysis to BDI time-series. It used a trigonometric regression to reflect data periodicity. It predicts annual growth of BDI by using various global economic indices, and raw-material indices as dependent variables. It also found strong cyclical patterns in BDI between 3 to 5 years and used it as the dependent variable to predict BDI. The results showed significant performance gain in prediction when compared with exclusion of cyclical patterns. They performed a risk management experiment with 12-month-ahead forecasts to make an investment in BDI and could carry out best performances compared to other models applied (auto-regressive, rolling-window approach, and time-series momentum method). Bakshi, Panayotov, and Skoulakis (2012) identify a correlation coefficient between various economic indicators and BDI through rigorous literature reviews. Then, it predicts stock and commodity indices by using a three-month growth rate of BDI by Generalized Autoregressive Conditional Hetero-skedasticity (GARCH) model with the error variance in BDI time-series volatility. The study argued the predictability of economic indicators and stock market indices through BDI growth rate. They pointed that it is due to the movements or growth rate of indices reflecting the current state of world traded raw-materials that have positive effects which are directly influenced to the real-economy. It also concluded with the gradual diffusion of information (time-lag) that transferred from oscillation of BDI to real-economy which means, the possibility of its utilization as a lagging indicator. Tsioumas, Papadimitriou, Smirlis, and Zahran (2017) using exogenous variables to develop a multi-variate Vector-Autoregression (VAR) for prediction of BDI and compared predictive power with uni-variate ARIMA model. The proposed model outperformed the ARIMA approach. The distinction point of this research is that they were using a composed index as an input variable named Dry Bulk Economic Climate Index (DBECI) that was invented by Tsioumas (2016). The index is composed of eight sub-indicators that are economically related in the sector of consumers, liquidity, and industrial activity. The results approved that the index helps to improve forecasting accuracy that are only restricted in the given research environment. Study of Guan et al. (2016) showed BSI (sub-index of BDI) prediction based on one of the machine learning algorithms named Support Vector Machine (SVM). SVM is originally invented for supervised learning with classification of labelled inputs. The application of its variations for regression problems is called Support Vector Regression (SVR). The original SVR only concerns the difference in subset of each pair of training data point. Therefore, they used Least Squares Support Vector Machine (LS-SVM) which is appropriate for minimizing a cost function of difference in the whole hypothesis space for observed and target data points. Uni-variate (BSI) prediction with the usage of hybrid multistep prediction model is conducted. It is a combination of advantages of a direct (build a separate models with day-by-day) prediction model and an iterative (a single model with iteratively using an output of $(t-n+1)_{th}$ model as an input of next iteration) prediction model. The research could derive outperformed LS-SVM with the approach while compared with prediction results of other models named History Mean Prediction (HMP), Auto-Regressive Moving Average (ARMA), and the simple iterative prediction LS-SVM. Han, Yan, Ning, and Yu (2014) employed wavelet transform to denoise volatilities in BDI time-series that arise from random incidents in the dry bulk market. Then, monthly forecasting is performed with SVM and Genetic Algorithm (GA) introduced to hyper-parameter optimization. The results compared with three different models that named VAR, ARMA, and ANN.[9] The proposed method showed outstanding results and they could find possibilities to use for forecasting short-term trends of BDI. The thesis of Goulas (2010) examined a prediction of Baltic Exchange indices and freight futures by using various statistical models. Through the prediction, they could succeed with trading strategies on the freight futures that based on rolling window and interval (bootstrap) forecasting methods. Cullinane, Mason, and Cape (1999b) employed ARIMA model. It argued with whether significant changes are made or not before and after the exclusion of BHSI as a sub-index of BFI.[10] There were no significant statistical differences between the models. This and the other study (Cullinane, Mason, & Cape, 1999a) of the same authors made a short-term prediction with $AR(3)$ and $AR(2)$ models for uni-variate BFI. Yonghui, Yuwei, and Hualong (2014) showed forecasting to the other sub-index Capesize. They predicted BCI daily return rate with $GARCH(1,\ 1)$ model. Authors argued that time-series of BCI daily return rate follow statistical distributions of leptokurtosis and fat-tail fluctuation. They concluded with the model in a 1-day ahead forecasting.

9) The research was not stated which model used for ANN, it seems MLP employed.
10) The objective period of the research was 1993 which is before the revision of the index made.

3.2. Artificial Neural Network Architectures Based Prediction of Baltic Dry Index

Not a lot of researches in the discipline of prediction BDI by ANN architectures exist. Zeng, and Qu (2014) & Zeng, Qu, Ng, and Zhao (2016) used EMD and ANN to forecast BDI time-series. It decomposed BDI time-series into short-term and long-term trends. Then, they tried forecasting with ANN to construct EMD-ANN model. The model compared with prediction results of ANN and VAR. EMD-ANN model was outperformed. The latter research showed the same processing using EMD and ANN forecasting. However, it added another approach called Extent (or improved) Empirical Mode Decomposition (EEMD) that the authors invented. EMD method was applied to time-series data first, and then reconstitution process added to combine decomposed series into specific components named, high frequency, low frequency and long-term trend series. It also used ANN to make a forecast for each component. They utilized MLP with three layers. However, EEMD-ANN did not outperform EMD-ANN. The authors said it was due to the composed components containing different volatility frequencies that make it tough for ANN to learn intrinsic patterns. However, the process of EEMD is still worth to retain the original economic nature of BDI time-series. Leonov and Nikolov (2012) investigated specific routes of Baltic Panamax 2A and 3A. They developed a hybrid model of wavelets transforms and ANN. Wavelet transforms for decomposition for BDI time-series into term of volatilities with different wavelet transformed time frequencies during the given research period. They utilized ANN for time-series forecasting like the other researches. They forecasted each time frequencies from the decomposed form first, and then reverse composition into one time-series with predicted values. The results compared with GARCH model. The hybrid model showed outstanding results. The researchers argued that wavelet transforms approach for data preprocessing is able to control the dynamicity of volatile data, which can assign advantages to learning intrinsic patterns of given datasets by ANN during the training process. Uyar, Ilhan, and İlhan (2016) applied Recurrent Fuzzy Neural Network (RFNN). Contrary to vanilla ANN, FNN can handle linguistic rules as prior knowledge rather than taking numeric inputs. There are mainly two approaches for training FNN. First is back-propagation learning algorithms like most of ANN models do. Second is Genetic Algorithm (GA) to determine fuzzy connection weights and biases while minimize cost (error) function. The authors argued that RFNN should be implemented to overcome disadvantages of FNN that represented the model generally give dynamics or temporal solutions. For forecasting Long term Freight Rate Index (LFI) they presented GA based trained RFNN. The results showed outstanding performances of the model while compared with various statistics-based models such as ARIMA, Holt-Winters, and so forth.

There were relatively less studies conducted with ANN-based approaches for the forecasting of BDI time-series. However, it is clear that applications of ANN are successful in various fields of studies with other time-series. For the other bulk shipping market such as tanker market was also forecasted with ANN-based applications (Kavussanos, & Alizadeh-M, 2002; Li & Parsons, 1997; Lyridis, Zacharioudakis, Mitrou, & Mylonas, 2004).

Also studies in specific time-series rather than shipping industry, such as financial, economics, short and long term stock market, spot market, and many others showed outperformed applications of ANN-based approaches (Fadlalla & Lin, 2001; Kuan & White, 1994; Peter Zhang, 2012; Saad, Prokhorov & Wunsch, 1996, 1998).

3.3. Findings and Limitations

Only few studies could be found that used ANN-based approaches for forecasting BDI while there are many others exist with statistics-based approaches. However, still worthiness of ANN-based approach is approved by many other fields of studies for time-series forecasting. Findings from the literature reviews were summarized as follows:

- BDI is very highly dependent on world economics. Therefore, the forecasting of its time-series is meaningful not only in academics but also in practical applications in the both microscopic and macroscopic perspectives of from the dry bulk shipping market to whole shipping markets, and even world economics related.

- BDI has special characteristics that refer to cyclicity, seasonality, and volatility. The literature reviews showed various approaches for overcoming dynamicity of the dry bulk shipping market and forecasting with statistics and ANN models.

- ANN-based approaches are appropriate for handling non-linearity and volatility while mapping or learning intrinsic hidden patterns, which means that it is reasonable to use ANN applications to time-series forecasting, especially, BDI time-series.

- Applied models introduced in the literature reviews outperformed rather than basic models. It means that exploring and applying various methodologies should be implemented for handling dynamicity of BDI time-series like other applications in real world problems.

All the ANN applications for BDI or related time-series forecasting reviewed from the thesis showed different level of performances. It is hard to compare due to the differences in research environments (e.g., basic premises or assumptions, periods of the studies, subjects of time-series, preprocessing methods, single or hybrid or multi-dimensional approaches, selection in various ANN models, etc.). Therefore, it is impossible to compare the researches unless applying completely same set-ups for all the prerequisites of researches. No one can easily conclude that applying a particular methodology for any given time-series or data is the right answer. Consequently, there is no guarantee that the models with good performances in a particular time-series will show a similar performance in other time-series datasets. Due to the nature of the time-series data that varies over time, even if the model is performing exclusively in a particular periods of time-series, it will not guarantee the same performances in future situations. Therefore, application of various models and experimental studies are inevitable.

The ANN has a limit of 'black-box model' because the results of learning revealed with meaningless values of weights in the presence of a hidden layer. In other words, it is difficult to understand exactly what the model means by the numerical values presented, and it is essential for fine-tuning to be preceded in hyper-parameters for training ANN up to a certain level. Nevertheless, it is used in many researches and practices while showing outstanding performances in problems with difficulty finding exact solutions. It can even rule out statistical baselines. In addition, the applications of ANN let researchers adjust the degree of non-linearity according to its structures as needed. So, it is suitable for predicting nonlinear and highly volatile data such as BDI time-series.

The applied ANN models to predict BDI in the literature reviews have structural limitations that did not take into account the conditions of past trends or events that may persist in the future, which is the basic assumption of time-series prediction. Therefore, the thesis will apply RNN architectures designed to consider sequential events that occurred over time. In addition, LSTM was also applied to find out applicability to BDI time-series. LSTM is a kind of recurrent structure neural network which overcame the limitation of RNN that named vanishing or exploding gradient problem of the learning gradient. The details of each model will be discussed in the next chapter. This thesis is significant in that it is the first research to apply vanilla RNN and LSTM to specific time-series (BDI).

Chapter 4 Research Methodologies: Autoregressive Integrated Moving Average Model and Artificial Neural Network Architectures

Chapter 4 will illustrate employed methodologies. It is not only for the purpose of introducing both conventional statistical model and MLP in ANN architectures, but also includes the relatively newly developed one of the variants of RNN model named LSTM. ARIMA model will only be briefly illustrated. Both RNN and LSTM will be discussed more thoroughly to emphasize the objectives of the thesis. Note that all the algorithms will be given is implemented for the invoked models in the thesis.

4.1. Autoregressive Integrated Moving Average Model

ARIMA is a generalization form of a model, so-called Auto-Regressive Moving Average (ARMA). ARIMA model outperformed in various fields of econometrics and particular in time-series analysis. It is fitted to time dependent data either to boost the understanding of internal movements or trends of data or predict future points in the sequences. As like many other conventional statistical models, ARIMA model is also under the circumstances of fundamental assumptions of statistics (e.g., linearity, normality, and equality of variance, and so forth). Depending on its own internal structures of the model, it also assumed input data exists in both 'non-stationary' and 'non-seasonal'. There are various applied models that exist, such as Seasonal ARIMA (SARIMA), Vector ARIMA (VARIMA), Fractional ARIMA (FARIMA), X-12-ARIMA, and so forth, which are transformed or modified with their suitability of the specific defined problems.

A non-seasonal ARIMA model will be applied to a uni-variate time-series forecasting in the thesis. It follows the Box-Jenkins model. The model is usually analyzed through time-series by the following standard three-step algorithms. Note that the standard algorithms are revised with the invoked models in the thesis. BDI time-series is too volatile to fit by the non-seasonal ARIMA model over the research periods. It was hard to stabilize only with log-transformation and differencing. Therefore, volatile periods are omitted so that is only limited periods of time-series from January 4, 2010, to December 23, 2016. The forecasting will be made 30-days ahead (From January 3, 2017, to February 13, 2017).

1) Model Identification:

For accurate analysis, the following assumptions are made for the given time-series data. It is 'securing stationarity' and 'eliminating trend and seasonality'. In the case of data that is non-stationary, log-transformation is usually performed to ensure uniform distribution of time-series (*Formula 2*). To eliminate seasonality, it can be conducted with calibration of BDI time-series data by differencing. The time-series was stabilized after the first-order differencing. First-order differencing will be calculated between consecutive observations from BDI time-series where t is the single data point of a day in the given time-series (*Formula 3*). The results of log-transformed and then first-order differenced time-series is *Figure 1*.

$$BDI_{time-series}\,Y\{y_{t+1} \in given\ \ periods\} \ = \ \log(y_{t+1}) \tag{2}$$

$$y_t^{'} \ = \ y_t \ - \ y_{t-1} \tag{3}$$

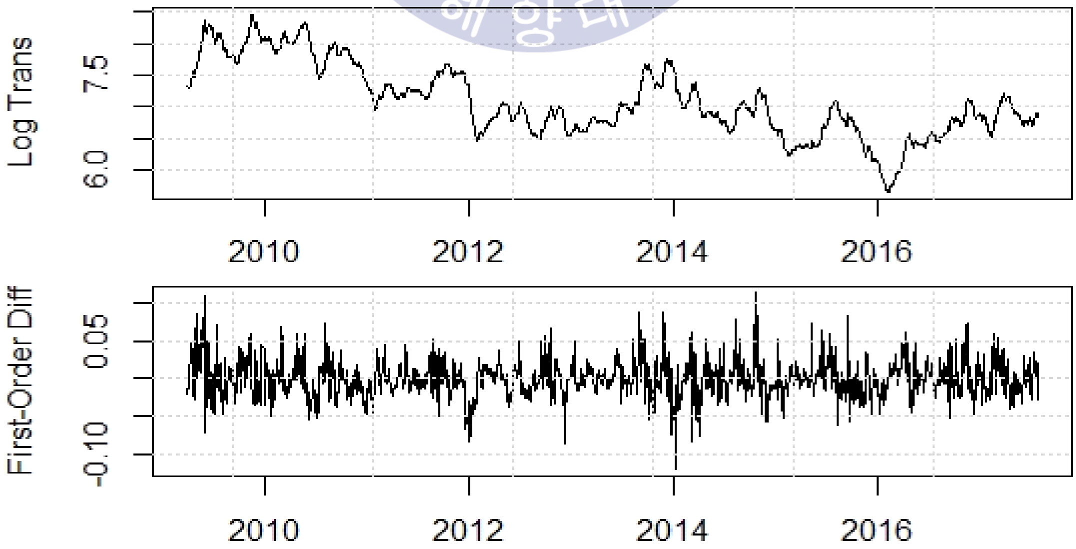


Fig. 1 First-order differencing of log transformed BDI time-series

At this stage, $(0,\ d,\ 0)$ is determined where from ARIMA $(p,\ d,\ q)$. Non-seasonal ARIMA model is generally denoted as *Formula 4*.

$$ARIMA(p,\ d,\ q) \tag{4}$$

$$\begin{aligned} &where \\ &\ p\ =\ Order\ of\ the\ autoregressive\ model \\ &\ d\ =\ Degree\ of\ differencing \\ &\ q\ =\ Order\ of\ the\ moving\ average\ model \\ &p,\ d,\ q\ \geq\ 0 \end{aligned}$$

2) Parameter estimation:

Order of the autoregressive moving average $(p,\ q)$ (ARMA) is determined by using an Auto Correlation Function (ACF) and a Partial Autocorrelation Function (PACF). At this time, each order is selected based on a parsimonious manner that can be explained as simply as possible within the range where each model satisfies the p-value $(p \leq .05)$ while no correlation exists within its lags.

3) Model verification

Check whether the residuals are appeared as normality for the obtained model $(p,\ d,\ q)$ by the parameter estimation. The residuals at this time are independent of each other and the mean and variance must be uniform over time. If it is not achieved, further processing for stationarity and parameter tuning in the first and second steps of algorithms might be needed. Akaike Information Criteria (AIC) and Baysian Information Criteria (BIC) are implemented for comparing quality of fit across the appropriate combinations of degrees of $AR(p)$ and $MA(q)$. Finally, the model is chosen with a certain level of fitting that is $AR(1)$ and $MA(1)$ with the first-order of difference $I(1)$ which is non-seasonal $ARIMA(1, 1, 1)$ model (*Formula 5*). The 30-days ahead forecasting by the settled model will be executed and discussed in the next chapter.

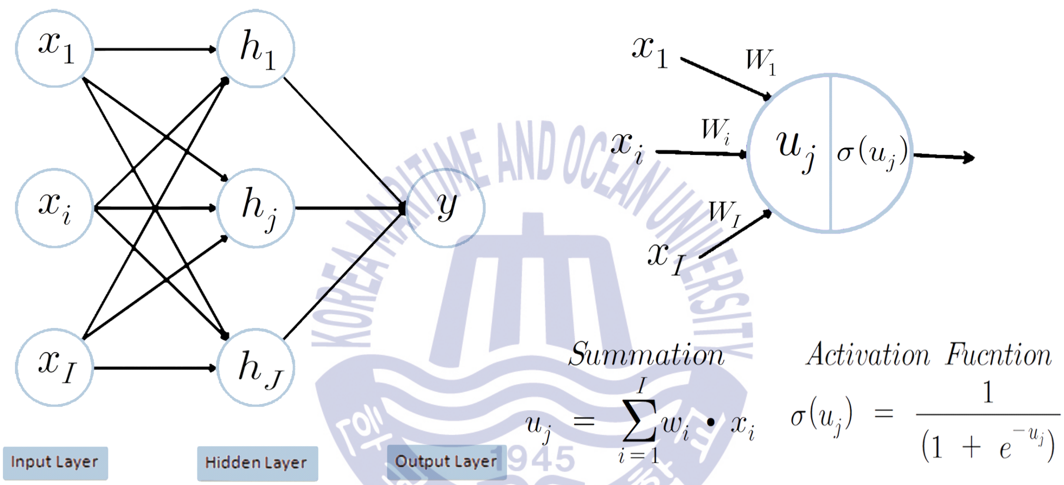
$$\Delta y_t = \Delta\alpha_1 \Delta y_{t-1} + \beta_1 \epsilon_{t-1} \qquad (5)$$

$where$
$\Delta y_t = y_t - y_{t-1};\ first-order\ diffrencing$
$\alpha_t = autoregressive\ model$
$\beta_t = moving\ average\ model$
$\epsilon_{t-1} = white\ noise\ error$
$t = daily\ data\ point\ of\ given\ time-series$

4.2. Artificial Neural Network Architectures

4.2.1. Multi-Layer Perceptron

MLP is composed of more than three layers of input, hidden and output layers and it contains nodes in each layer. Their ability of approximating extremely complex problems is proven by Universal Approximation Theorem. The theorem explained by Csáji (2001) is as follows "... *the standard multi-layer feedforward networks with a single hidden layer that contains* *finite number of hidden neurons, and with arbitrary activation function are universal approximators in* $C(\mathbb{R}^m)$." This means that it can approximate any continuous functions on compact subsets of real number $\mathbb{R}^m$. The model also has the advantage of being able to learn without the need for simplifications of the problem because it does not require prior assumptions of traditional statistics. Plain MLP (*Figure 2*) will be applied in the thesis.



$$u_j = \sum_{i=1}^{I} w_i \cdot x_i \qquad \sigma(u_j) = \frac{1}{(1 + e^{-u_j})}$$

Fig. 2 Multi-Layer Perceptron with sigmoid activation function

Normally, MLP utilizes a supervised learning. The supervised learning in a regression problem of MLP is the task of learning a function approximation that maps relations between input and output vectors in the hypothesis space. In general, to train MLP, the back-propagation learning algorithm is used. The algorithm is a series of steps to decide the strength of connections between the nodes by updating weights. The weights are calculated by error derivatives with gradient descent algorithm to minimize an error between input and output vectors. And then it propagates the errors to the reverse direction and updates the weights of the network. Gradient descent is the algorithm that is generally used for searching an optimal solution of a minimum error with efficiency in computation cost. It calculates the solutions by derivative of error function with the chain rule in differentiation. Generally, it uses the least-mean-square as the error function of weights update rule, especially in a regression problem. The steps of the back-propagation learning algorithm with gradient descent weights update rule is summarized as follows.

The back-propagation learning algorithm:

1. Random initialization of weights (W_0) with small values

2. Feed forward the input vectors through the layer

For each input-output pair ($\vec{x_i}$, $\vec{y_i}$), $\vec{x_i}$ is feed forwarded through input-hidden-output layers of the network and compute the output $\hat{y_i}$ (*Formula 6*).

$$input(net) = \left(W_0 + \sum_{i=1}^{I} W_i x_i \right) \tag{6}$$

$$hidden(net) = \sigma(u_j) = \left(W_0 + \sum_{j=1}^{J} W_j \bullet \left(W_{0j} + \sum_{i=1}^{I} W_{ij} x_i \right) \right)$$

$$output(net) = \left(W_0 y_0 + \sum_{i=1}^{K} W_i y_i \right)$$

where
W_0 = *corresponding weight matrix*
i, j, k = *output of each layer*

During every iteration of the learning algorithm, before passing the values to the output layer, the hidden layer calculates its input values u_i (from the output of input layer nodes) with its own activation function. The activation function in nodes of hidden layers is playing a role as thresholds that only pass a certain level of values between the nodes of input and output layers. In this thesis, a sigmoid function is applied as the activation function for MLP (*Formula 7*).

$$\sigma(u_j) = \frac{1}{(1 + e^{-u_j})} \tag{7}$$

3. Calculate a loss function

For supervised learning, it is using the sum of squared error (SSE) as the error function. It calculates the difference between the input-output pair. The objective function of MLP is to minimize the SSE error function (*Formula 8*).

$$E^{(i)} = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H}(o_{lh} - y_{lh})^2 \tag{8}$$

$where$
$o_{lh} = output\ of\ corresponding\ nodes\ in\ output\ layer$
$y_{lh} = target\ output$
$lh = input - output\ pair = (1,\ ...,\ L), (1,\ ...,\ H)$

4. Calculate derivatives of the error function with back-propagation

For the formula induction, partial derivatives of the learning process by chain rule was omitted. The update rule is simple. If the error decreases $\left(\frac{\partial E^{(i)}}{\partial W_k^{(i)'}} < 0\right)$, as the weight increases, the learning algorithm tends to increase the weight values. Otherwise, if the error increases $\left(\frac{\partial E^{(i)}}{\partial W_k^{(i)'}} > 0\right)$, as the weight increase, the learning algorithm tends to decrease the weight values. New weight $W_k^{(i+1)}$ is updated by the *Formula 9*.

$$W_k^{(i+1)} = W_k^{(i)} - \eta \cdot \frac{\partial E^{(i)}}{\partial W_k^{(i)'}} \tag{9}$$

where
η = *learning rate*
$E^{(i)}$ = *calculated output of defined error function*

5. Iterate the algorithms until convergence

The series of algorithms are implemented iteratively as many times as needed until it is converged with the weights that to achieve a minimum error between the pairs of input and output vectors. Note that the found weights do not always guarantee a global minimum solution.

4.2.2. Recurrent Neural Network

The basic idea of RNN was first proposed by Jordan (1986). It was designed for natural language processing, which occurs sequentially. The other name of it is Jordan Net. It is also composed of multi-layer neural networks. During the learning process of the network, calculated values of past series of inputs will be influencing calculation values for future series of inputs.

It is the existence of a 'state unit' that makes RNN unique. Let U_h is the state unit that is composed of a set of matrix or vectors. The output of the state unit connects and hands over the values to the input layer. At each time step of t, updates of the networks occurred with both the values of state unit at previous time step $(t-1)$ and the sequential input vectors at t toward the input layer at the same time. The values of the state units are derived from the nodes of the output layer that represents the relationships between the value of the output layer $y_{(t-1)}$ and the value of the input layer x_t. The matrix of U_h is used in the calculation of weights update rules for the vector of x_t, *where* $t \in \mathbb{N}$ *and* $t \geq 1$ at the time step t recursively. Let W_h is a set of weights in the hidden layer that corresponds to x_t. The learning process is performed on which point of time to receive more influence depending on the magnitudes of W_h and U_h among the input variable x_t and the output variable $y_{(t-1)}$. b_h and b_y are the bias-terms that occur in the connections between the hidden and the output layer, respectively. σ_h and σ_y are the activation function in the hidden and the output layer. According to the notations, the following formula can be expressed (*Formula 10*).

$$\begin{aligned}&\textit{Jordan Network}\\&h_t = \sigma_h(W_h x_t + U_h y_{t-1} + b_h)\\&y_t = \sigma_y(W_h h_t + b_y)\end{aligned} \tag{10}$$

On the contrary, Elman (1990) suggested a ‘context unit’ to the recurrent network architecture that differs from Jordan network. The context unit is the independent layer that consists of nodes. It is connected to the hidden layer with a value of 1, initially. During the learning process of the model, the values of the hidden layer $h_{(t-1)}$ are stored in the context unit while each iteration of updating the network. The stored values in the context unit are multiplied by the values of hidden layer h_t that will be represented as a matrix or vectors of parameter value of $U_h = h_{(t-1)} \cdot h_t$. The specified process is occurs as the very first step of the learning process before the each of the iterations. Compared to the Jordan network, there is a difference in that weight adjustment occurs between the input variable x_t and the values of hidden layer $h_{(t-1)}$, not depending on the magnitudes of the both values of W_h and U_h among the input variable x_t and the output variable $y_{(t-1)}$. Again, as like Jordan network, b_h and b_y are the bias-terms that occur in the connections between the hidden and the output layer, respectively. Also, σ_h and σ_y are the activation function in the hidden and the output layer. According to the notations, Elman network can be expressed into the following *Formula 11*.

$$
\begin{aligned}
&Elman\ \ Network \\
&\quad h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h) \\
&\quad y_t = \sigma_y(W_y h_t + b_y)
\end{aligned} \tag{11}
$$

In conclusion, Jordan and Elman network is basically based on recurrent or recursive structure, which is a learning sequences that depends on the elapse of the time. However, Jordan network only learns from the memory of the output layer at the previous time steps that feed to the input layer together with newly appeared input sequences sequentially. On the other hand, existence of the context unit makes Elman network special. Values of the output layer and the hidden layer are calculated independently and simultaneously for each of the iterations of learning process. Due to the difference in the structures, Elman network has the advantage of adjusting memory and forgetting better than Jordan network according to the weights of the past events. Therefore, Elman network shows better performance in a relatively long sequential datasets. When comparing RNN to MLP, in a basic feed forward neural network, it is presupposed that each input variable has no influence on each other independently. Therefore, the function approximation for a given hypothesis space is learned only by the sum of the corresponding values and the dot product at the current or temporal time step. On the other hand, RNN models are useful for learning sequential data because the previous events are memorized and reflected during its learning process (Budcema & Luigi Sacco, 2000; Sutskever, Vinyals, & Le, 2014). The RNN architecture can be depicted as *Figure 3*. The right side of the figure shows unfolded recursive structures of RNN that with arbitrary given time steps.

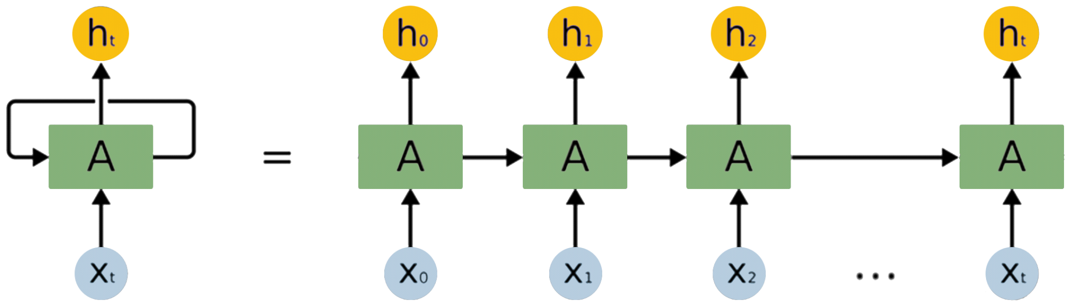


Fig. 3 Unfolded Recurrent Neural Network

Elman network updates its weights with a learning algorithm called Backpropgation Through Time (BPTT) (Werbos, 1990). The fundamental learning object is performed in the same way as the back-propagation algorithm that minimizes errors by adjusting weights in connections. The difference from the conventional back-propagation is that all the error terms from the current time step t to all past time steps $(t-n)$ are considered for each of the iterations of learning. Inevitably, an increase in the size of given time steps or inputs is meant by deepening network structures, and it causes the exploding or vanishing gradient problem. This issue will be discussed further in the next section. In this thesis, Elman network is implemented, which is more frequently used in practice due to the structural advantages, and its learning algorithm BPTT can be defined as follows (Guo, 2013). Some of the notations have been modified.

The BPTT learning algorithm:

In this thesis, for supervised learning, using the sum of squared error (SSE) as an error function in the output layer (*Formula 12*) and using the sigmoid function as an activation function in each node of the hidden layer (*Formula 13*).

$$E_y^{(t)} = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H}(\hat{y}_{lh}^{(t)} - y_{lh}^{(t)})^2 \tag{12}$$

where

$\hat{y}_{lh}^{(t)}$ = *output of output layer at* (t)

$y_{lh}^{(t)}$ = *target output at* (t)

lh = *input−output pair* = $(1, \ldots, L), (1, \ldots, H)$

t = *time−step*

$$\sigma(x_t) = \frac{1}{(1 + e^{-x_t})} \tag{13}$$

From the output layer to the hidden layer, the weight $W_k^{(t+1)}$ can be updated as follows (*Formula 14*).

$$W_y^{(t+1)} = W_y^{(t)} - \eta^{(t)} \bullet \frac{\partial E_y^{(t)}}{\partial W_y^{(t)}} \tag{14}$$

where

η = *learning rate*

$E_y^{(t)}$ = *calculated output of defined error function*

Let, U is a weight matrix of the context unit that was derived from the previous hidden layer to the current hidden layer. τ is an arbitrary number of time steps. It can be calculated as follows (*Formula 15*). The formula back-propagate the sum of error values over the given period of time while with derivatives of the error function.

$$E_j^{(t-\tau-1)} = d_j(E_j^{(t-\tau)} \bullet U,\ t-\tau-1) \tag{15}$$

$$\begin{aligned} &where \\ &d_j(\bullet) = d_{jh}(x,\ t-\tau-1) = xf'(net_h) \\ &h = hidden\ layer(t) \\ &j = previous\ hidden\ layer(t-1) \end{aligned}$$

Let, V is a weight matrix from the connection between the input and hidden layer. Now, newly updated weight matrixes of V and U at next time step $(t+1)$ can be calculated as follows (*Formula 16*).

$$\begin{aligned} V^{(t+1)} &= V^{(t)} + \eta \sum_{\tau=0}^{T} x^{(t-\tau)} \bullet E_j^{(t-\tau)^T} \\ U^{(t+1)} &= U^{(t)} + \eta \sum_{\tau=0}^{T} h^{(t-\tau-1)} \bullet E_j^{(t-\tau)^T} \end{aligned} \tag{16}$$

4.2.3. Long Short-Term Memory

The exploding or vanishing gradient problem in gradient-based learning methods remarkably occurrs in conventional RNN structures. It is due to the calculation of the partial derivative of the error function. The calculations are being processed iteratively by dot products and additions of vectors through all the past time of the given space. Therefore, as deepening in the network structure occurs, weight vector with a decimal values cause the vanishing gradient problem and otherwise, weight vector with an excess of 1 cause the exploding gradient problem (Hohreiter, Bengio, Frasconi, & Schmidhuber, 2001). Consequently, due to such a structural problem, there is a limit in the structural advantage of the RNN due to possibilities of incompleteness in learning.

Hochreiter, and Schmidhuber (1997) invented a recurrent structure of ANN named Long Short-Term Memory (LSTM) network that overcame the limitations of RNN. The difference from RNN model is that it consists of 'cells' with several 'gates' that exist in each single cell. The gates are namely an 'input gate', an 'output gate', and 'forget gate' with various activation functions in each gate. Note that the forget gate was introduced by Gers, Schmidhuber, and Cummins (1999). The 'cell state' that integrates and conveys the output of the corresponding gates to next cell is located at the top of the corresponding gates. The cell state of the network C_t at the current time step of t learns from the previous cell state $C_{(t-1)}$ at $(t-1)$ with calculation results of the gates (input, output and forget gates) at t and hidden weights of the previous cell $h_{(t-1)}$. Then the results is aggregated in the current cell state level C_t and finally, that will be conveyed to the next cell state as a $C_{(t+1)}$ at very next time step of $(t+1)$ and also the same process happens for the hidden weights h_t as a $h_{(t+1)}$. The processes are being executed iteratively until finishing feeding and learning the all the given datasets for the network. Based on the basic LSTM, the forget gate contains a sigmoid activation function. Depending on characteristics of its activation function, output of the forget gate is between 0 and 1. The input variables of the gate are dot product of input data x_t and hidden weights of the previous cell $h_{(t-1)}$. The closer the output of the gate is to 1 means that the previous hidden state has more influence on the current cell state

C_t and if the value reaches to 1 represents 'completely memorizing', otherwise the value closer to 0 means that has less influence and if the value reaches to 0, it represents 'completely forgetting'. The corresponding output of the gate is multiplied by element-wise product to the cell state C_t. The input gate is a stage of learning a degree of memorization for newly given input data. It also considers same input as forget gate which is x_t and $h_{(t-1)}$ but with different activation functions. The gate basically contains both the sigmoid and a hyperbolic tangent function.[11] Calculations in the gate are being processed independently by the two given activation functions. For the sigmoid function, completely identical calculations as in the forget gate are being processed, while the hyperbolic tangent function pushes the values through between (-)1 to 1. The final output of the gate is a multiplication of the values generated from both activation function of the corresponding gate by element-wise product. And then, the output will be conveyed to the cell state C_t by calculation of vector addition. As the hyperbolic tangent function can derive the values of range between (-)1 to 1, it can sustain the values longer in time dependency structure of LSTM. The implementation of the function means that the replacement of forgetting memories introduces a newly put hypothesis space to the network. At this stage, the completely calculated values of the C_t is passing to the next cell state as $C_{(t+1)}$. Lastly, the output gate exists to determine the output of the cell by the input x_t and the weights of hidden state $h_{(t-1)}$ to the current cell state C_t. For the calculation of the output gate, completely calculated

11) The choice of activation function can vary depending on the user's purpose. It is not only applicable to LSTM but also to other ANN models.

C_t is filtered by the hyperbolic tangent and element-wise product with sigmoid filtered of the dot product between the input x_t and the weights of hidden state $h_{(t-1)}$. The final output of the gate is being a vector of hidden weights of the current cell state h_t. It also passes through the next cell state as $h_{(t+1)}$. The purpose of the gate can be interpreted as the role of conveying past information and useful information that newly updates at the current cell state to the next cell state. $W_{f,i,o}$ and $b_{f,i,o}$ are the weights and bias-terms of the corresponding gates. σ_g and σ_c are the activation function of sigmoid and hyperbolic tangent respectively. According to the notations, LSTM can be expressed into the following *Formula 17*.

$$\begin{aligned}
&\textit{LSTM Network} \\
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_c(c_t)
\end{aligned} \tag{17}$$

In this thesis, hard sigmoid function was used instead of the sigmoid function. The function is a piecewise linear approximation of the sigmoid function. It has the advantages of low computing costs while keeping the properties of the sigmoid function. The hyperbolic tangent function is still used in the same place for the network. Both formulas are as follows (*Formula 18*[12] and *19*).

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12) Courbariaux, M., Hubara, I., Soudry, D., El-Yaniv, R., & Bengio, Y., 2016. Binarized neural networks: Training deep neural networks with weights and activations constrained to +1 or −1. *arXiv*, preprint arXiv:1602.02830, p. 2.

$$x_t^b = \begin{cases} +1 \ \ with \ \ probability \ \ p = \sigma_g(x_t) \\ -1 \ \ with \ \ probability \ \ 1-p, \end{cases} \tag{18}$$

where

$$\sigma_g(x_t) = clip(\frac{x_t+1}{2}, 0, 1) = \max(0, \min(1, \frac{x_t+1}{2}))$$

$$\sigma_c(x_t) = \frac{\sin(x_t)}{\cos(x_t)} = \frac{e^{x_t} - e^{-x_t}}{e^{x_t} + e^{-x_t}} \tag{19}$$

As shown in the above algorithm description, LSTM is a special case of RNN structure that the gates are added. In other words, it can learn the long-term dependencies in the input sequences by its selectiveness in memorization and forgetting terms. It allows gradients to flow through the network without change. This partially solves the problem of the vanishing gradient problem, which is considered to be a limitation of RNN, and enables learning of complex patterns. In addition, the role of the gates allows us to better simulate the efficient way in which the human-brain actually learns and remembers. As evidence of this, applications of LSTM in various fields have recently been developed and actively applied to natural language processing, machine translation, image processing, time-series prediction, and the like (Sutskever, Vinyals, & Le, 2014; Vinyals, Toshev, Bengio, & Erhan, 2015). Note that exploding gradient problem can still possibly occur in LSTM network. The vanilla LSTM can be depicted as *Figure 4*.

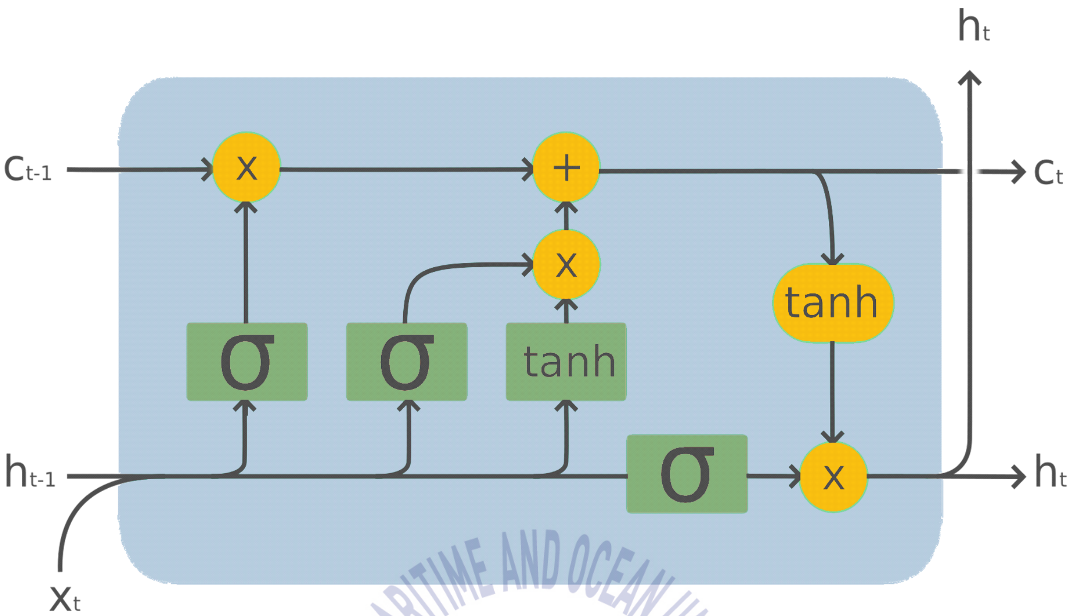

Fig. 4 Long Short-Term Memory

LSTM also updates its weights by the BPTT algorithm as like RNN to minimize errors on a set of training sequences. However, due to the existence of the gates in LSTM, the algorithm update the weights of each gate back through all the corresponding gates in arbitrary given time periods. It means that leads to an enormous increase in computational costs and again, that can cause another vanishing or exploding gradient problem while deepening in networks structures. To solve such the problem, the modified version of the BPTT algorithm that named Truncated Back-propagation Through Time (TBPTT) can be the one solution. It is known as the most practical method for training RNN architectures. According to Sutskever (2013), "... *it is more adept at utilizing temporal dependencies of longer range ... . It processes the sequence one time step at a time, and every* k_1 *time steps, it runs BPTT for* k_2 *time steps, so a parameter update can be* *cheap if k_2 is small. ... its hidden states have been exposed to many time steps and so may contain useful information about the far past, which would be opportunistically exploited.*" It is all about the learning efficiency of the algorithm and partially dealing with vanishing or exploding gradient problem. For the details of the algorithm see the studies of Williams and Peng (1990).

4.3. Basic Assumptions and Data Descriptions

The recent form of BDI time-series was being announced since November 1, 1999. There was a difficulty in gathering pair set (daily matched with other time-series) of time-series across other used time-series. Hence, in the thesis, even with the abundance of data points, only restricted periods of time-series will be used. All the time-series used in the thesis covers approximately 9 years of data points from April 1, 2009, to July 31, 2017, so 2080 days of data points are gathered.[13] All of the ANN models of applications will perform in multi-variate predictions that feed 8 variables as inputs for training and fitting to the 1 variable (BDI). So it can be defined as a 'many to one' prediction problem. Usage of various types of time-series and datasets that are related to the world economy status can be found from the studies of the literature reviews. Even some of the works of literature focused on to predict BDI itself, the selections or preprocessing methods on the datasets are varied depending on their own taste in

13) Note that BDI time-series is announced daily basis only with business days while exclusions of holidays of British.

somehow. The time-series data used were maritime business related, especially those that are likely to influence BDI. Therefore, in the thesis, the input variables that are associated with BDI were selected as follows (*Table 3*). Additionally, time-series of BCI, BPI, BSI, and BHSI are also included for BDI prediction as some of the literature that utilizing BDI sub-indices as a predictor of BDI. From *Figure 5* to *7* illustrate the time-series datasets used. Note that the plots were depicted separately due to the ranges of the values much different from each other.

Table 3 Descriptions of time-series datasets

Time-series datasets[14]	Descriptions
Baltic Dry Index (BDI)[1)15)]	Composition index of the four sub-indices (Target variable to predict)
Baltic Capesize Index (BCI)[2)]	Sub-index of BDI for specific size of bulk carrier (100,000 DWT and above)
Baltic Panamax Index (BPI)[3)]	Sub-index of BDI for specific size of bulk carrier (65,000 ~ 99,999 DWT)
Baltic Supramax Index (BSI)[4)]	Sub-index of BDI for specific size of bulk carrier (40,000 ~ 64,999 DWT)
Baltic Handysize Index (BHSI)[5)]	Sub-index of BDI for specific size of bulk carrier (10,000 ~ 39,999 DWT)
Bunker Price Index (BIX)[6)]	Average Global Bunker Price (AGBP) for all individual port prices (US$ / Metric Tonne)
Total bulk carrier deliveries[7)16)]	Total delivery amounts of cargoes by bulk carrier (DWT)
Clarksons Average Bulker Earnings[8)]	Average bulker earnings ($/Day) (covers all bulk vessel types)
ClarkSea Index[9)]	A weighted average index of earnings for the main vessel types[17)] ($/Day)

14) For readers' legibility, all the origins of the resources have submitted at the *endnotes* of the chapter.

15) The gathered datasets [1), 2), 3), 4)] from the company's (©Quandl Inc.) Web site are that they only imported BDI and other related sub-indices from the Internet resources. They stated that the original resources came from ©Informa plc. (Lloyd's List). From the terms of use of Quandl, they make no claim to own the data it indexes or caches.

16) The author of this thesis has obtained the datasets from the listed resources that in the *endnotes [7), 8), 9)]* of this chapter. Those were collected through legal paths. The author declares that those were and will be used only for academic purposes. And also, complies with 'ANNEX2-PART1: ATTRIBUTION AND DISSEMINATION REQUIREMENTS' in the terms and conditions of Clarkson Research Services Limited Online Systems. Korea Maritime and Ocean University (KMOU) does not define a particular page to cover such the statement so it has recorded at *endnotes* of the chapter.

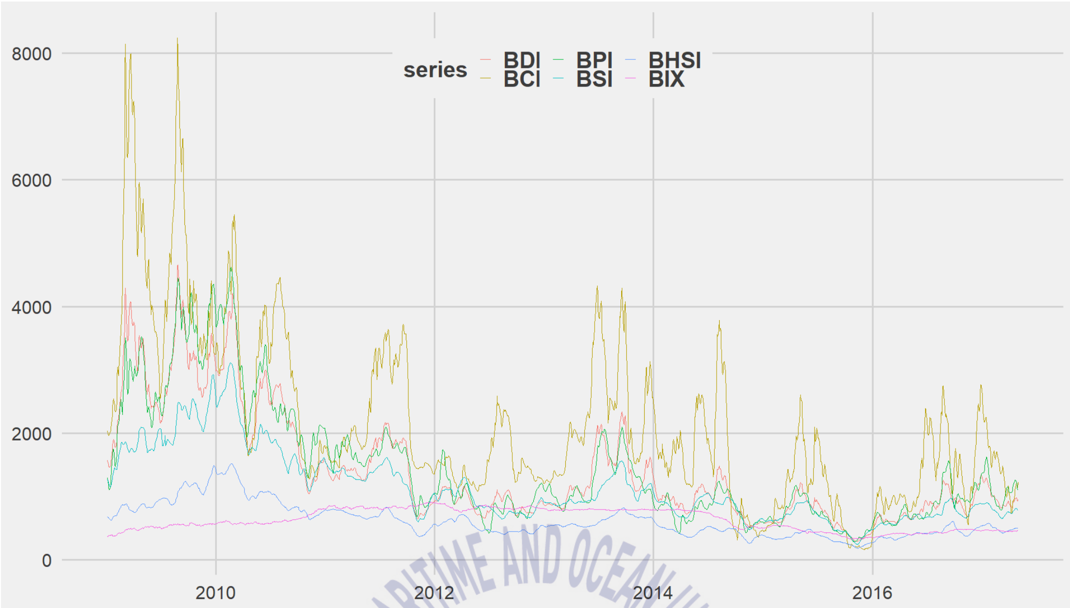

Fig. 5 BDI, BCI, BPI, BSI, BHSI, and BIX (From April 1, 2009, to July 31, 2017)

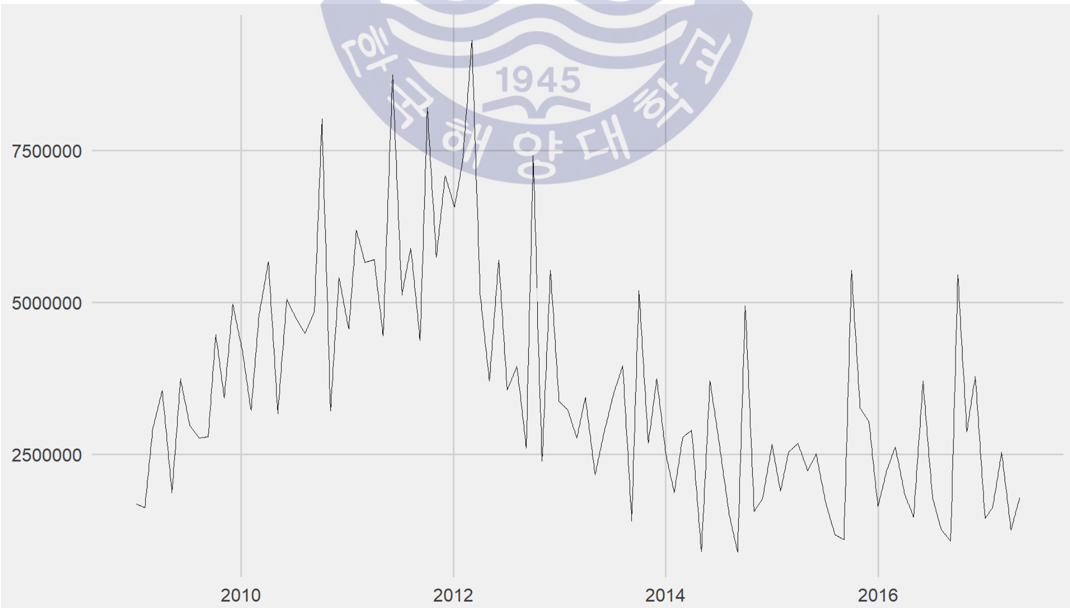

Fig. 6 Total bulk carrier deliveries (DWT) (From April 1, 2009, to July 31, 2017)

17) The weighting method is based on the number of vessels in each fleet sector.

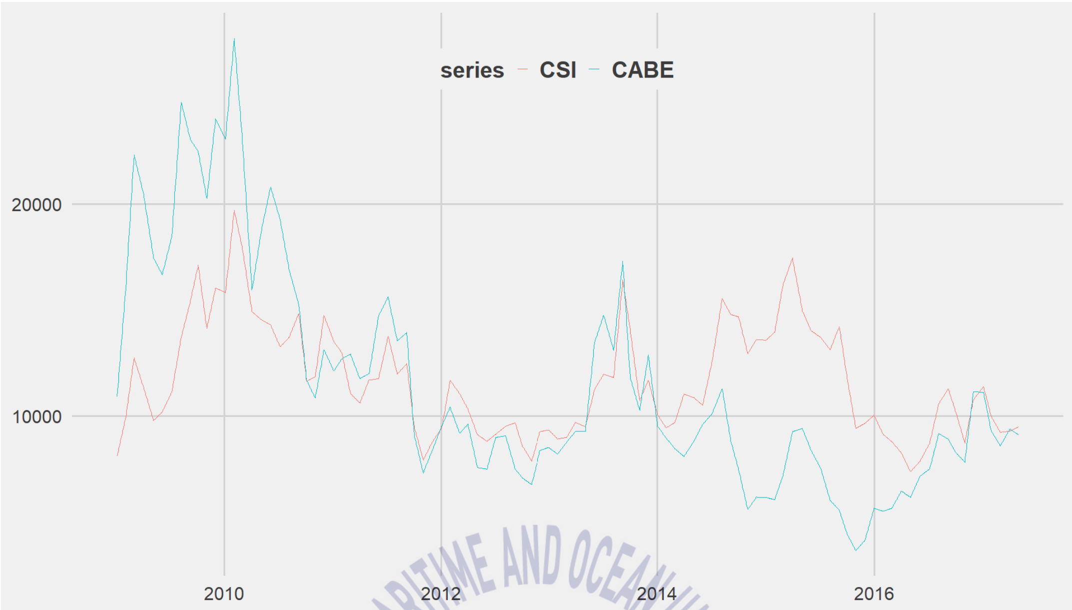

Fig. 7 ClarkSea Index and Clarksons Average Bulker Earnings ($/day) (From April 1, 2009, to July 31, 2017)

As stated, the thesis is concerned with the periods of BDI between April 1, 2009, to July 31, 2017. During the periods between January 2, 2007, and July 1, 2009, BCI has been concerned both voyage-charter and time-charter average at the same time. Therefore, it may seem that further pre-processing is needed for BDI and other time-series used in the thesis. The further pre-processing may derive more precise experiments results of ARIMA and ANN models. Nevertheless, the thesis pre-assumed that only normalization is enough to predict BDI so it will take a place as the preprocessing method on all the given time-series. This belief came from the faith that it can capture the hidden patterns of a given hypothesis space as the universal approximator which belongs to the ability of endemic architectures of ANN models. Still, the objective periods does not include the data that occurred after the 'big' re-examination in early 2018.[18)]

For simplification of the problem, unlikely the other studies of literature, there is no further preprocessing methodologies (e.g., statistical and econometrical methods, feature engineering, etc.) that took place on given time-series datasets, except data normalization. Before training all of ANN models, all the data will be normalized with 'min-max normalization'. It compresses and maps the input range between 0 to 1 or (-)1 to 1. The selection of the normalization range can differ depending on its own purpose. In this thesis, normalized range between 0 to 1 will be applied to all the given time-series. It has an effect of squashing the number values of hypothesis space (not the absolute hypothesis space to search, only the numeric values are squashed) that will be learnt by ANN. This derives much faster in gradient descent convergence. It also has a purpose for preventing dominance that occurred by smaller or larger values from the mean of given datasets during a training process. The formula of min-max normalization is as follows (*Formula 20*).

$$z_i = \frac{x_i - min(x_{t \in all})}{max(x_{t \in all}) - min(x_{t \in all})} \tag{20}$$

$where$
$x_i = x \in t = (x_1, x_2, \ldots, x_n)$
$z_i = i^{th}\ normalized\ data\ point$

18) After March 1, 2018, BDI was re-examined and BHSI is excluded. Baltic Exchange concerned that it makes no more significant difference to the market. Originally, since July 1, 2009, it was equally weighted average (e.g., 25% of weighted average applied for every indices and adjusted with a constant multiplier). However, after the re-examination, 40% of BCI, 30% of BPI, and 30% of BSI with a constant multiplier of 0.10 is being announced. During the periods under which this thesis is studied, the corresponding changes in BDI are not included.

Some of the literature performed normalization training and test datasets with the same values from whole datasets. This thesis aims to construct a robust ANN model for the real-world problem. It can be achieved by assumed the test datasets as 'unseen data'. So, in this case, normalization will be performed for the entire dataset only with the values from the training datasets.

ANN predictions will be split into two phases. The first is to just verify the 'goodness of fitness' of ANN models to BDI time-series whether it can be fitted by 8 selected variables as input variables. Training and test datasets will be conducted in a ratio of 7:3 (from April 1, 2009, to February 2, 2015, for the training set and from February 3, 2015, to July 31, 2017, for the test set). The second phase will be the daily forecasting by the sliding-window method. Every data point for the y variable will be intentionally put back 1-day. Where t is a specific day of data point in the scope of given periods. The set of x input variables at $(t-1)$ will be pointed to next day of the y variable at the point of t. Thus, ANN will learn the sequences or patterns of the y variable that will arise from the sequences of the x variables at $(t-1)$, which can be defined as a daily prediction. The daily prediction will be conducted for a 1-year (from August 1, 2016, to July 31, 2017). At this phase, the proposed structures of ANN models through the first phase will be re-used as like a part of backtesting strategy. That to confirm the generalization power of the trained networks against to different size or future time windows. As like the basic assumptions of the fundamentals of time-series analysis, in the thesis, it pre-assumed that the events (input variables) of the previous day will be reflected or continued into the next business day. Furthermore, it also assumed that ANN models which conformed with recurrent architectures have enough capacity to memorize or forget the information on time dependency. This is because the networks will learn the sequences which data points have more or less influence depending on whether it has occurred in past or relatively recent.

Several packages of R-programming were used for constructing the ANN models, and for deriving the results. In addition, the packages also include Keras deep learning library using the TensorFlow backend. All packages used are listed in the bibliographies.

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1) ©Quandl Inc., 2017. *LLOYDS-Lloyd-s-List-BDI* [Online] (Updated July 7, 2017) Available at: www.quandl.com/data/LLOYDS-Lloyd-s-List-BDI [Accessed July 10, 2017].
2) ©Quandl Inc., 2017. *LLOYDS-Lloyd-s-List-BCI* [Online] (Updated July 7, 2017) Available at: www.quandl.com/data/LLOYDS-Lloyd-s-List-BCI [Accessed July 10, 2017].
3) ©Quandl Inc., 2017. *LLOYDS-Lloyd-s-List-BPI* [Online] (Updated July 7, 2017) Available at: www.quandl.com/data/LLOYDS-Lloyd-s-List-BPI [Accessed July 10, 2017].
4) ©Quandl Inc., 2017. *LLOYDS-Lloyd-s-List-BSI* [Online] (Updated July 7, 2017) Available at: www.quandl.com/data/LLOYDS-Lloyd-s-List-BSI [Accessed July 11, 2017].
5) ©Fusion Media Limited., 2017. *Baltic-Handysize-Historical-Data* [Online] (Updated July 7, 2017) Available at: www.investing.com/indices/baltic-handysize-historical-data [Accessed July 7, 2017].
6) ©Bunker Index, 2017. *Bunker Index* [Online] (Updated July 7, 2017) Available at: www.bunkerindex.com/prices/indices.php [Accessed July 15, 2017].
7) ©Clarkson Research Services Limited., 2017. *Shipping Intelligence Network Database: Total Bulk Carrier Deliveries* [Online] (Updated July 7, 2017) Available at: sin.clarksons.net [Accessed August 14, 2017].
8) ©Clarkson Research Services Limited., 2017. *Shipping Intelligence Network Database: Clarksons Average Bulker Earnings* [Online] (Updated July 7, 2017) Available at: sin.clarksons.net [Accessed August 14, 2017].
9) ©Clarkson Research Services Limited., 2017. *Shipping Intelligence Network Database: ClarkSea Index* [Online] (Updated July 7, 2017) Available at: sin.clarksons.net [Accessed August 14, 2017].

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Chapter 5 Results

As stated from the previous chapter, this chapter illustrates the results of the $ARIMA(1,\ 1,\ 1)$ model with 30-days prediction only in the given periods of BDI time-series. The results were transformed back with antilogarithm (exponential function) to depict the results with real numbers. For the results of ANN models, discussion of train-test (7:3) split place in the first, and then sliding-window method place in the second. The results of ANN models were transformed back with revert min-max normalization for plotting and comparing the results with real numbers. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were used for performance measurements to compare the prediction accuracy between the models in percentages.

The 30-days prediction by the settled model depicts in *Figure 8*. The plot was only illustrated with limited periods for readers' legibility. It showed very poor performances with numerical values of 1,000.002, 1,031.321, ..., 1,680.534 over time. It increases until before the 14 days of forecasting point. Even the original BDI time-series showed highly volatile fluctuations during the periods. In contrast, after 15-days of forecasting point, the values were flattened nearly 1,680. As discussed in previous chapters, non-seasonal uni-variate (BDI time-series) was only utilized. Remember that even though the purpose of implementing the model was only to emphasize outstanding performances of ANN architectures, there was also an underlying belief that the popular ARIMA model would have produced relatively good results too.

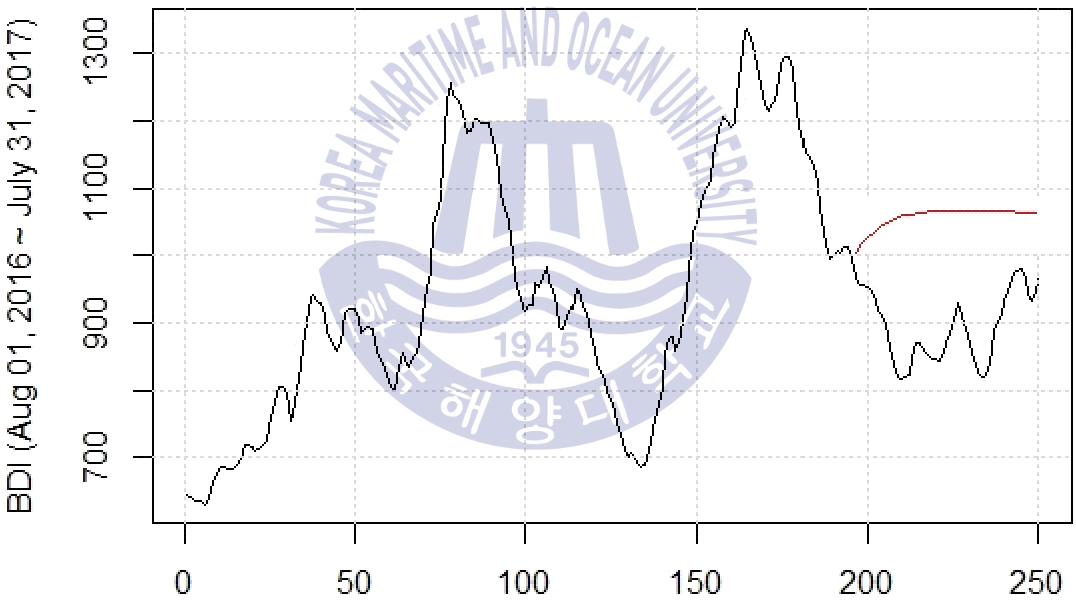

Fig. 8 Forecasted BDI time-series 30 days ahead by *ARIMA*(1, 1, 1) model (Forecasting from January 3, 2017, to February 13, 2017)

The results of train-test (7:3) split (from April 1, 2009, to February 2, 2015, for the training set and from February 3, 2015, to July 31, 2017, for the test set) was illustrated in *Figure 9* to *15*.

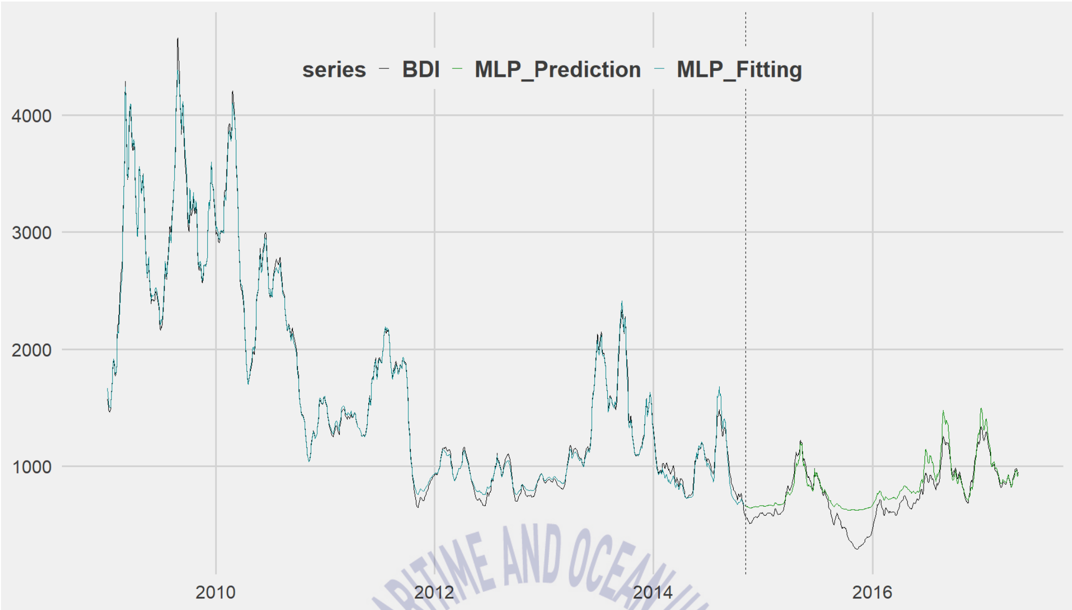

Fig. 9 Train-Test (7:3) split: Results of MLP

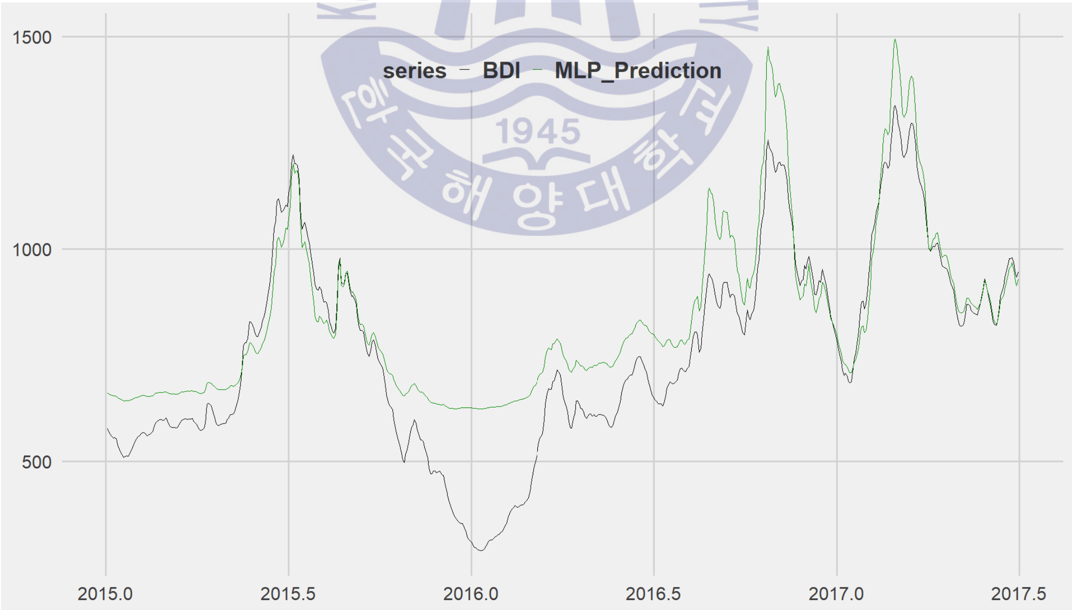

Fig. 10 Results of MLP fitting on the test set

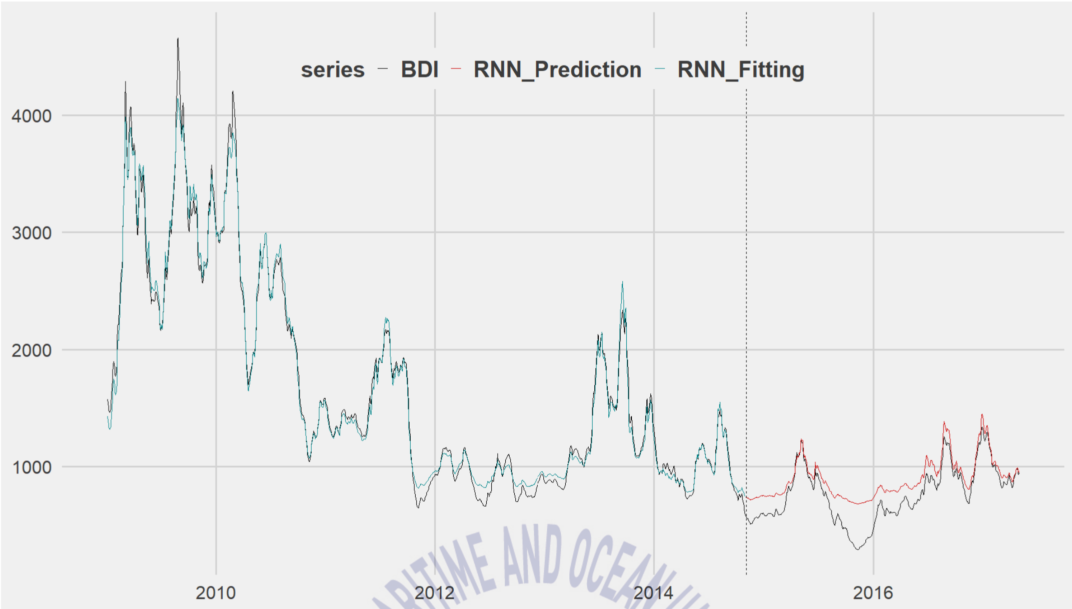

Fig. 11 Train-Test (7:3) split: Results of RNN

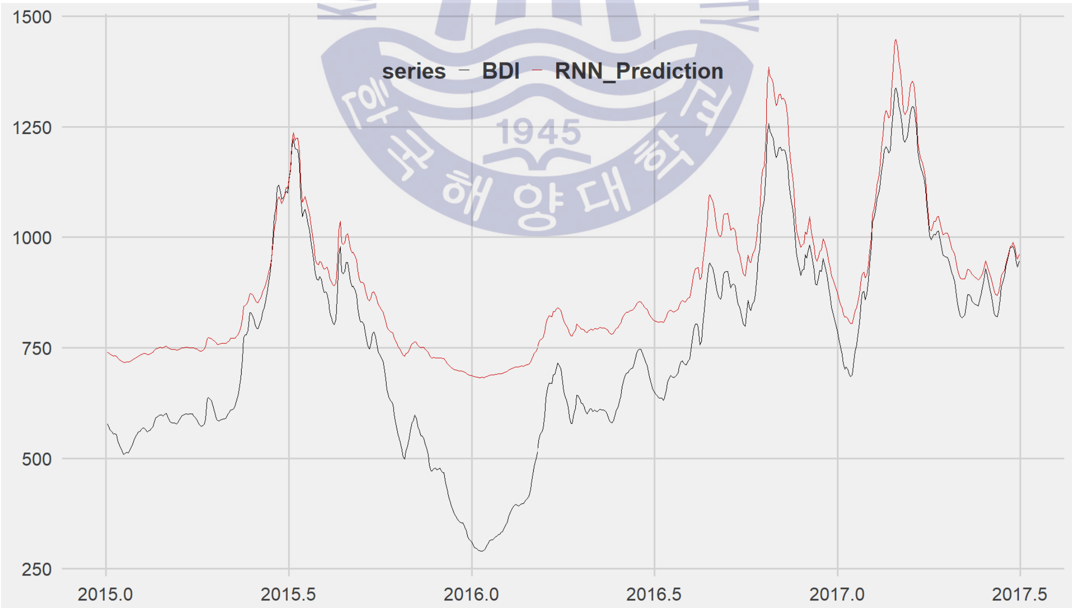

Fig. 13 Results of RNN fitting on the test set

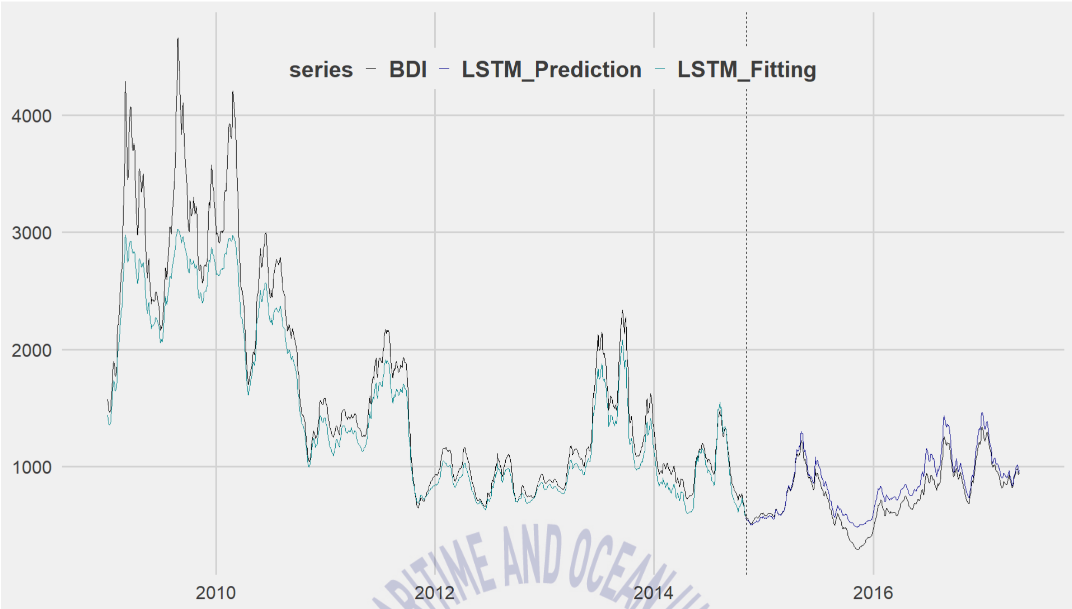

Fig. 14 Train-Test (7:3) split: Results of LSTM

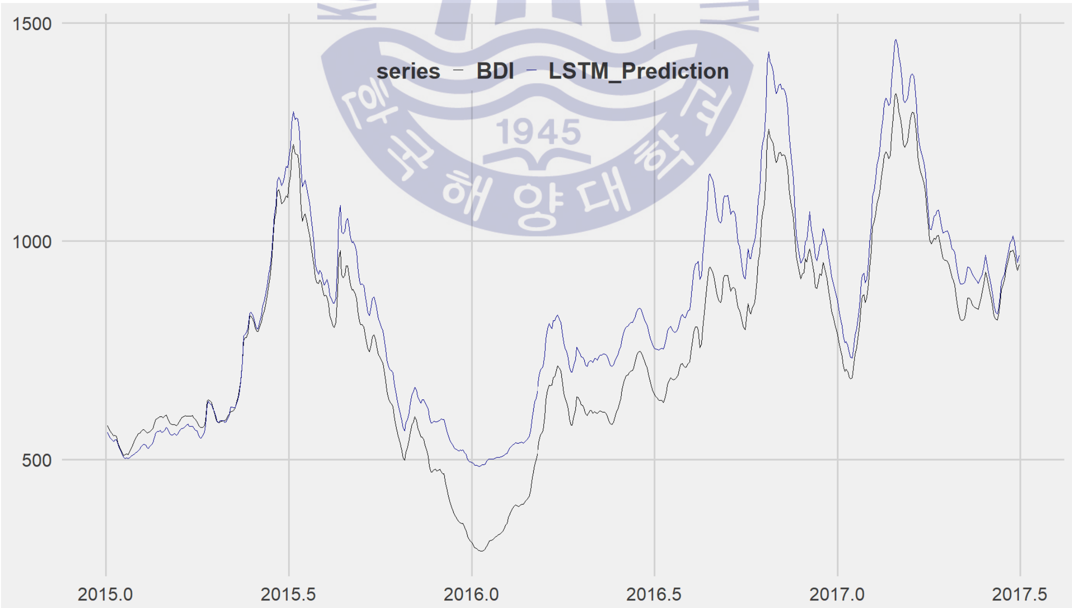

Fig. 15 Results of LSTM fitting on the test set

Note that ‘drop out’ and ‘recurrent drop out’ was applied to LSTM under the name of regularization technique for reducing over-fitting. For the details, see the studies of Gal and Ghahramani (2016). So it can be seen that the results of the *Figure 14* was not perfectly or nearly fitted to the training set, unlike other ANN models. As illustrated in *Figure 16*,[19] while LSTM is generally well fitting to BDI time-series over the periods of the test set, it is particularly well fitting to the trough stage than to other models. MLP showed moderate performances through the whole time. RNN showed the worst performance, but in some cases, it outperformed other models in certain sections of periods.

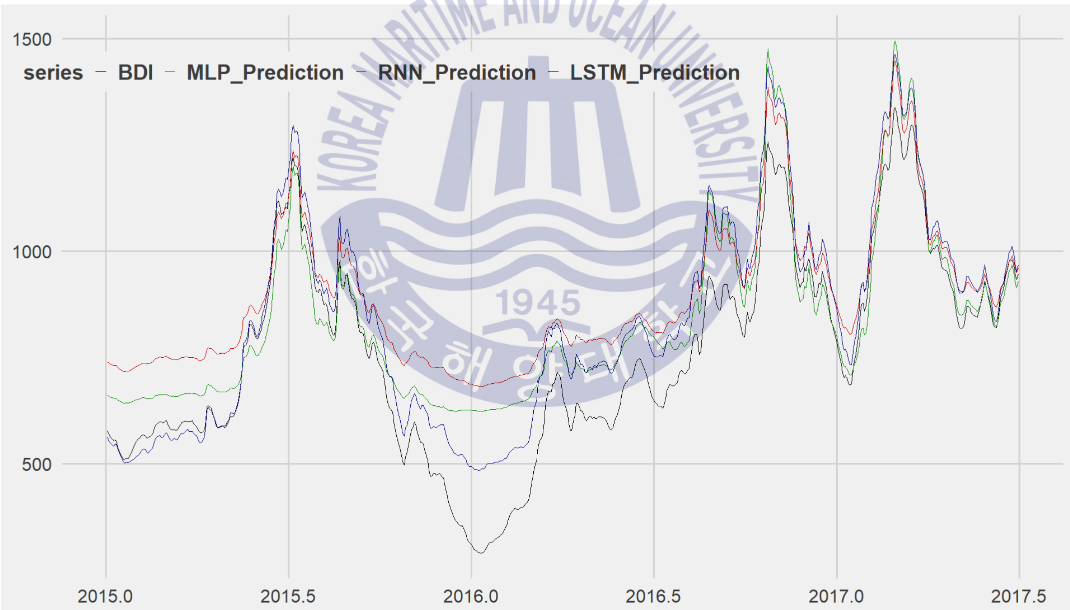

Fig. 16 Over-plotting the results of all ANN models fitting on the test set

LSTM showed outstanding results. Its MAPE was the lowest at about 14%, while others were 18% and 25%, MLP and RNN respectively. When compared MAPE between LSTM and RNN, there was a performance

19) For readers' legibility, the figure enlarged in the appendix.

improvement of around 11% in LSTM. However, in the case of between LSTM and MLP, only 4% of improvement in LSTM could be observed (*Table 4*).

Table 4 Results of comparing the prediction accuracy of each model based on LSTM

	MLP	RNN	LSTM	MLP/LSTM (%)[20]	RNN/LSTM (%)
MSE	15074.974	26438.01	10471.07	(+)43.968	(+)152.486
RMSE	122.780	162.598	102.328	(+)19.987	(+)58.899
MAE	95.853	134.977	87.129	(+)10.013	(+)54.916
MAPE (%)[21]	17.527	24.831	13.867	(+)3.66	(+)10.964

The thesis is not focusing on developing practical applications, but only for academical purposes. Therefore, it is unnecessary to concern efficiency of the training and prediction process. A number of layers and nodes of ANN models will be decided by 'trial and error' with parsimonious manner rather than using efficient algorithms for optimizing hyper-parameters such a random search, grid search, and the like. Determined structures of ANN models through the first phase of ANN predictions are summarized in *Table 5*. Remember that the settled model structures will be re-used in the second phase of ANN predictions to confirm how the determined model is well generalized to the unseen scenario.

20) To compare the prediction accuracy between LSTM and other models, the values of MSE, RMSE and MAE in columns labeled 'MLP/LSTM (%)' and 'RNN/LSTM (%)' were expressed as percentages of the differences between LSTM and other models.

21) MAPE is already calculated as the percentage of absolute value in the average of the difference between observed and predicted values. Therefore, only the differences of MAPE between the LSTM and other models were calculated.

Table 5 Network structures of ANN models

Hyper-parameters	MLP	RNN	LSTM
Normalization method	Min-Max [0 ~ 1]	Min-Max [0 ~ 1]	Min-Max [0 ~ 1]
Number of hidden layers or stacked LSTM	1 layer	1 layer	2 stacked LSTM layers
Number of nodes or cells in hidden layers	3 nodes	3 nodes	10 cells for each layer
Activation function	Sigmoid	Sigmoid	Hard sigmoid / Hyperbolic tangent
Learning algorithm	Back-propagation	Back-porpagation Through Time (BPTT)	Truncated Back-propagtaion Through Time (TBPTT)
Loss function	Mean Squared Error (MSE)	Mean Squared Error (MSE)	Mean Squared Error (MSE)
Recurrent drop out / Drop out	Not used	Not used	0.4 / 0.3

The results of daily forecasting for 1-year period with sliding-window method were illustrated in *Figure 17* to *22* (from April 1, 2009, to July 29, 2016, for the training set and from August 1, 2016, to July 31, 2017, for the test set).

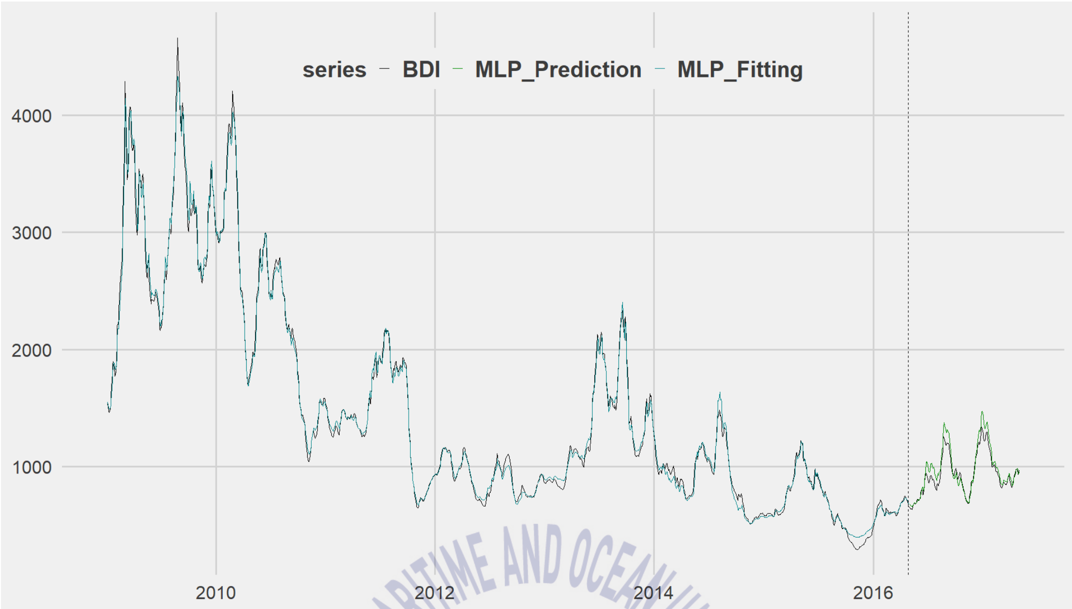

Fig. 17 Fitting MLP with sliding-window time-series

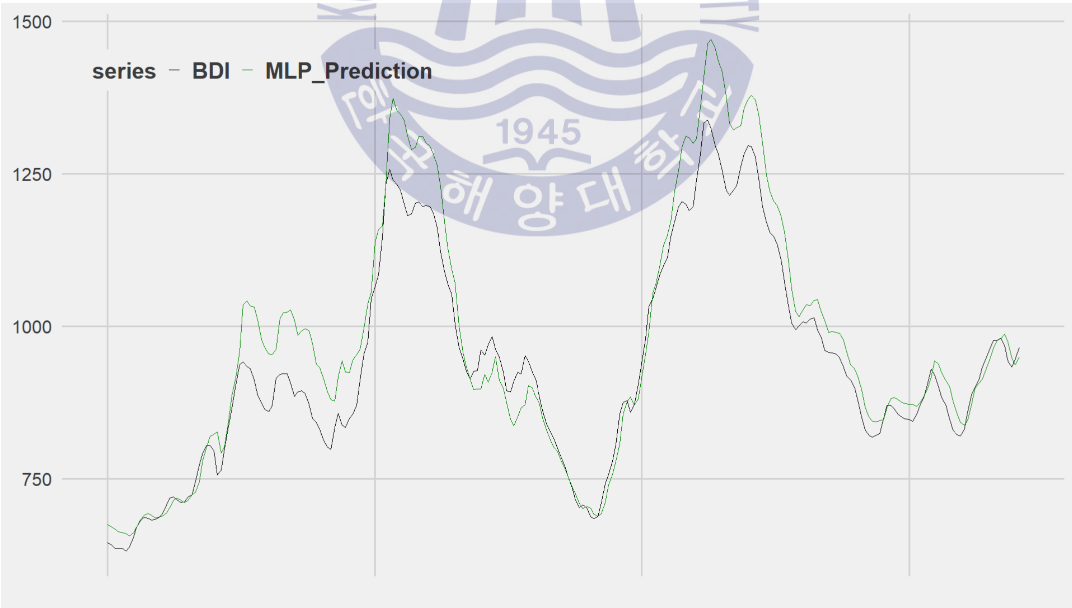

Fig. 18 Daily forecasting results of MLP for a 1-year (from August 1, 2016, to July 31, 2017)

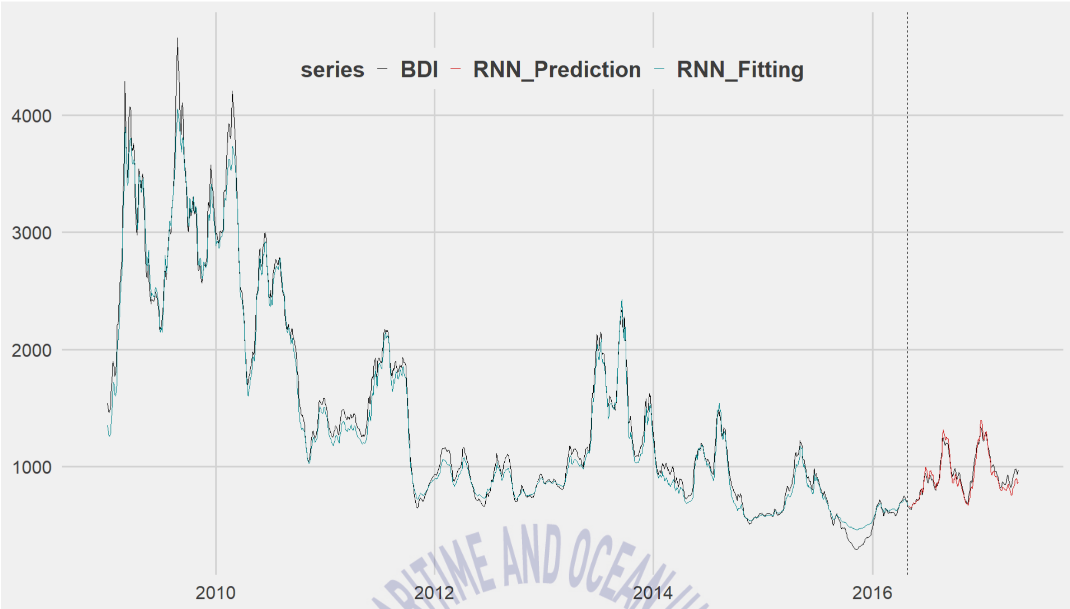

Fig. 19 Fitting RNN with sliding-window time-series

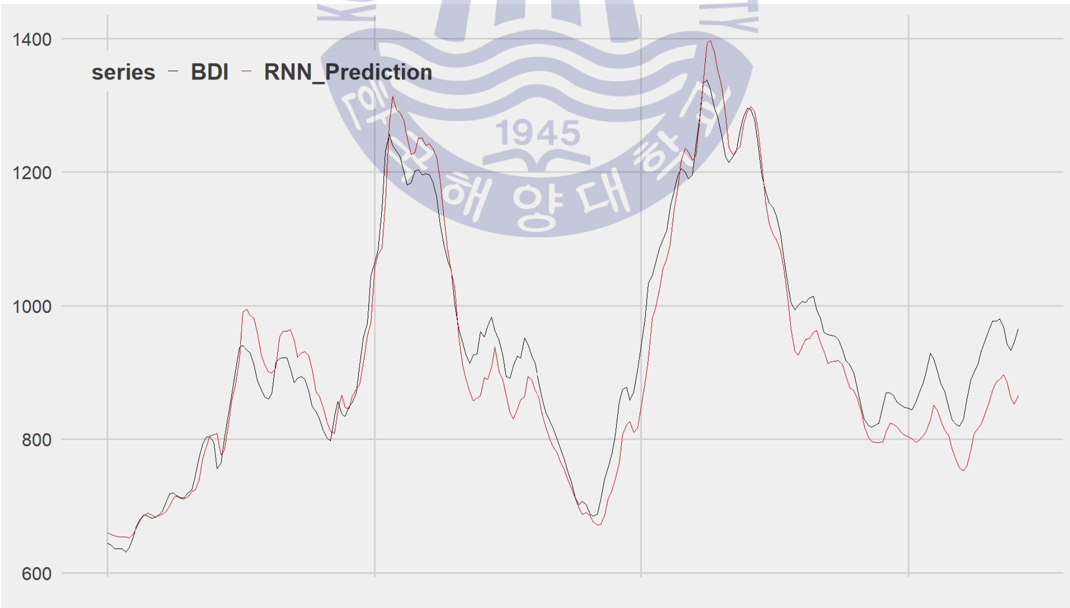

Fig. 20 Daily forecasting results of RNN for a 1-year (from August 1, 2016, to July 31, 2017)

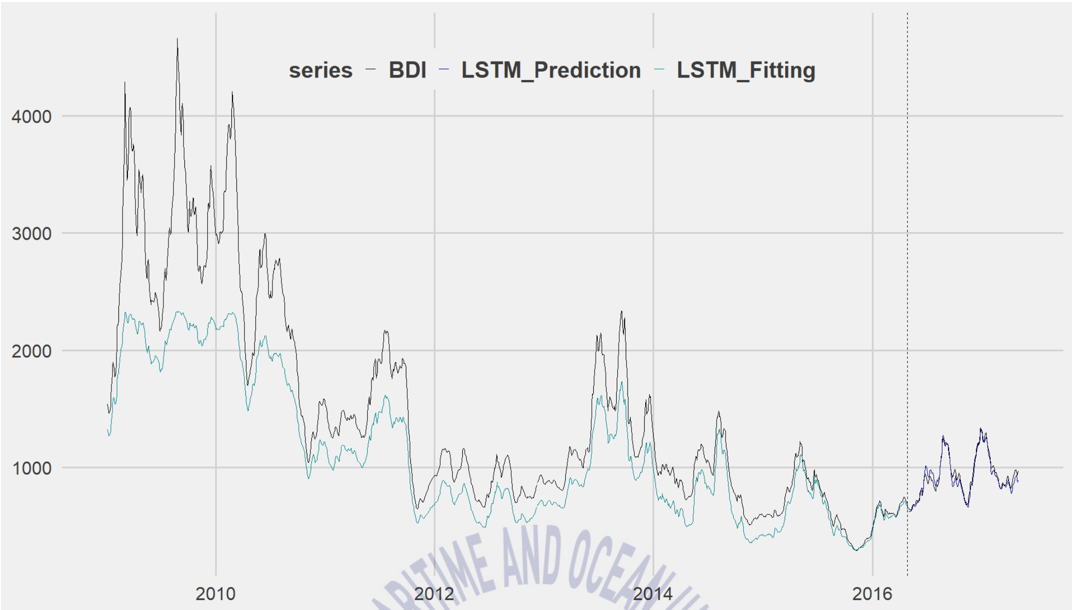

Fig. 21 Fitting LSTM with sliding-window time-series

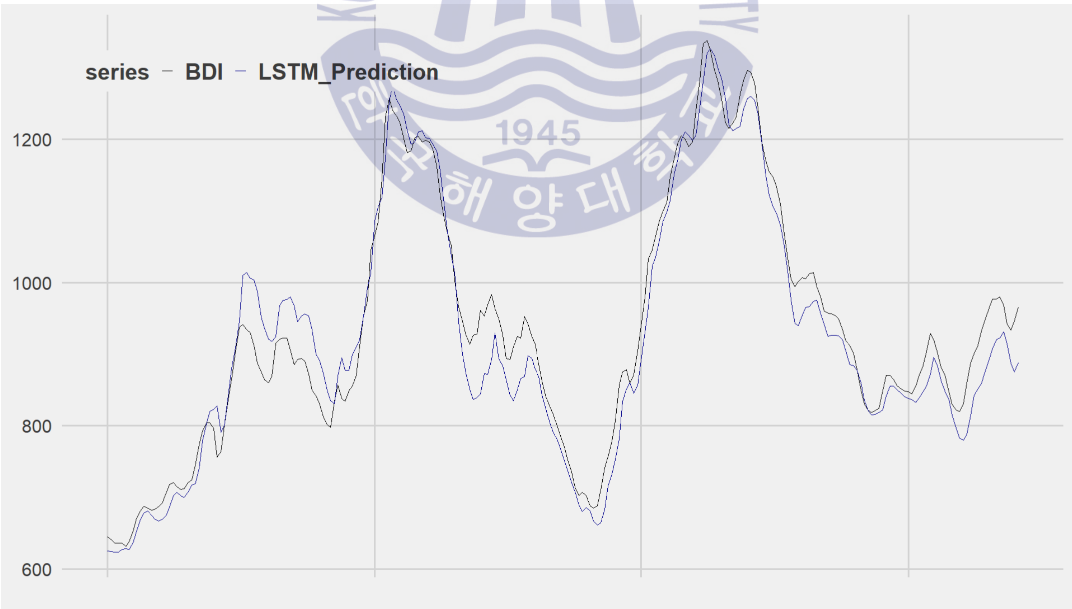

Fig. 22 Daily forecasting results of LSTM for a 1-year (from August 1, 2016, to July 31, 2017)

The results of *Figure 21* which may seem under-fitted to the training set is due to the regularization terms was applied. As illustrated in *Figure 23*,[22] unlikely the results of the first phase, LSTM was well fitting to both the trough and peak stage than to other models. At this time RNN showed moderate performances through the whole time while MLP does not. These results can be interpreted that RNN architectures have better generalization power than MLP. However, MLP showed predictions that very close to the actual value in certain periods after July of 2017. If a real-world application is considering the opportunity cost of the computational cost coming from the complexity of RNN architecture, MLP can be considered as a decent alternative. Even LSTM needed careful adjustment of the hyper-parameter to obtain a certain level of results.

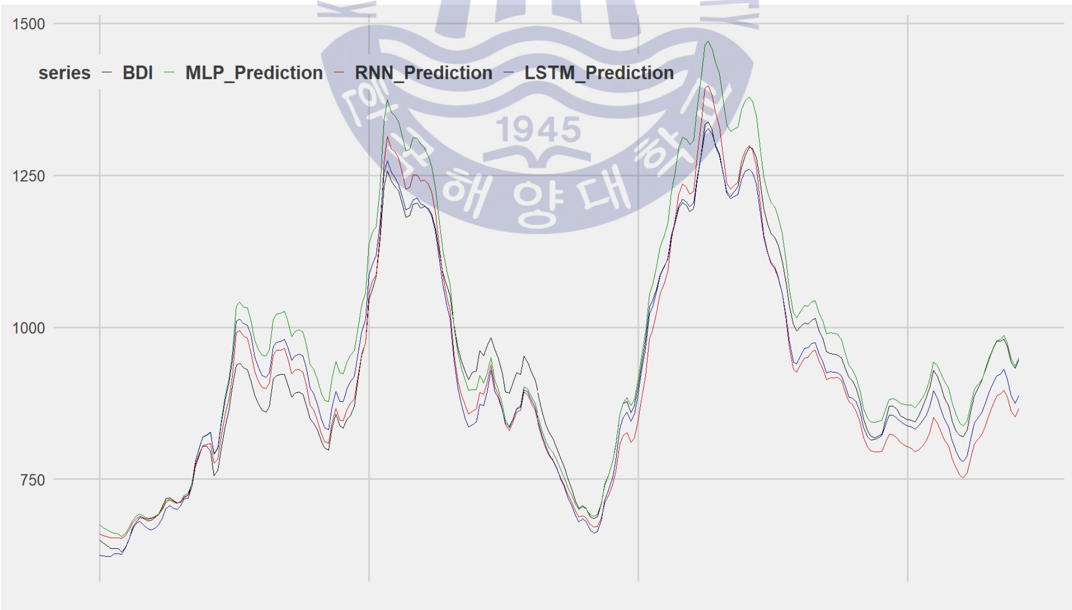

Fig. 23 Over-plotting the prediction results of all ANN models

22) For readers' legibility, the figure enlarged in the appendix.

LSTM showed outstanding results. Its MAPE was the lowest at about 3.5%, while others were 4.3% and 4.8%, RNN and MLP respectively. When compared MAPE between LSTM and MLP, there was a performance improvement of around 1.3% in LSTM. However, in the case of between LSTM and RNN, only about 0.7% of improvement in LSTM could be observed (*Table 6*). In the application of prediction, MAE also can be the most important figure. In practice, small errors can lead to sensitive consequences. The measurement is the absolute mean of difference between observed and predicted values. It shows average difference with positively transformed values. The value of MAE shown by LSTM can be interpreted to mean that the average real-estimated error value is within the range of the values (±32.518) during the research periods.

Table 6 Results of comparing the prediction accuracy of each model based on LSTM

	MLP	**RNN**	**LSTM**	**MLP/LSTM (%)[23]**	**RNN/LSTM (%)**
MSE	3920.055	2407.645	1644.688	(+)138.346	(+)46.389
RMSE	62.610	49.068	40.555	(+)54.383	(+)20.991
MAE	47.600	40.340	32.518	(+)46.381	(+)24.054
MAPE (%)[24]	4.798	4.278	3.544	(+)1.254	(+)0.734

23) The same conditions as stated in the 'citation 22)' have been applied.
24) The same conditions as stated in the 'citation 23)' have been applied.

Chapter 6 Conclusion

The purpose of this thesis was to study the prediction of BDI time-series by applying both statistics-based and ANN-based approach. Non-seasonal uni-variate ARIMA model applied for short-term prediction which showed poor performances. It mainly focused on building outstanding ANN models to forecast BDI time-series. However, take note that there are plenty of robust statistical methodologies to model ARIMA while improving prediction performances in a more precise manner. Therefore, this means that some head-rooms exist for further improvements in forecasting performances of ARIMA model. This point can suggest future research topics. For example, the results could be improved by using a seasonal and/or multi-variate ARIMA model which considers the seasonality or volatility of BDI time-series.

The applications of ANN models MLP, RNN, and LSTM were applied to predict relatively long-term periods with the sliding-window method as a daily prediction application. ANN applications showed outstanding performances with intentionally adjusted datasets with the sliding-window method. Especially, recurrent architectures of ANN showed better learning performance than MLP for specific time-series (BDI). In particular, LSTM showed the highest prediction accuracy. However, the complexity of the model was relatively high. The optimal configuration of the MLP structure has a lower-level of network architecture than the RNN but has shown consistent performance. Considering the opportunity cost of the computational cost coming from the complexity of RNN architecture, MLP can be considered as a decent alternative. Although the time taken for the learning process of the models was not recorded in the study, RNN was the slowest to complete the learning process up to achieve a certain level of convergence, followed by LSTM and MLP. The important point here is that only a 1-day sliding window method was applied for the empirical prediction of BDI. As discussed, RNN architectures have recursive structures and are known to have good performance to predict relatively long sequences. Of course, the learning process of ANN models were proceeded with whole past datasets, but only a daily set of variables were put through the learnt networks to predict the future point of 1-day ahead. Although the thesis designed the networks that showed the outstanding prediction results, it was an approach that does not fully utilize the ability of RNN that can be learning long-term sequences. As mentioned in other literature, other approaches can be actively used to carry out longer-term predictions rather than daily predictions. Also, the author of the thesis has selected variables with a naive approach. It can lower the precision of the thesis, even if there is certain straight intuition that the selected variables are likely to affect BDI. Various feature engineering based on machine learning techniques can be applied for selection or preprocessing of used time-series. Also, other techniques such as hyper-parameter optimization can improve the efficiency of training and increases the chance of finding the optimal solution. This can be another point for future research.

Nevertheless, this thesis is significant in that the BDI prediction was performed through a quantitative and scientific approach using ANN architectures. This is the very first study to apply RNN and LSTM to specific time-series data (BDI) and has proved the superiority of RNN architectures for the corresponding time-series. BDI plays an important role in the market. It is not only an indicator of the sole market condition itself but also utilized in other related markets. Furthermore, it is regarded as a leading indicator of world economic conditions due to the special characteristics of the market and carrying cargoes that differ from any other markets. Consequently, BDI reflects the dry bulk shipping market condition directly, which means that deep understanding of the behavior and future trends of the dry bulk shipping market with BDI can be the key-success for market dominance. Therefore, the prediction of BDI time-series can be utilized in many sectors of the industry. For instance, FFA trading, building and selling a vessel, strategic allocation of vessels, employment, rational investments, and optimum decision making with efficiency can be anticipated. Also, it can function as the auxiliary index to build or investment for port infrastructures, maritime human resources, national maritime business policies and so forth.

References.

Budcema, M., & Luigi Sacco, P., 2000. Feedforward networks in financial predictions: the future that modifies the present. *Expert Systems*, 17(3), pp. 149-170.

Chistè, C., & Van Vuuren, G., 2014. Investigating the cyclical behavior of the dry bulk shipping market. *Maritime Policy & Management*, 41(1), pp. 1-19.

Courbariaux, M., Hubara, I., Soudry, D., El-Yaniv, R., & Bengio, Y., 2016. Binarized neural networks: Training deep neural networks with weights and activations constrained to +1 or –1. *arXiv*, preprint arXiv:1602.02830, pp. 1-11.

Csáji, B. C., 2001. *Approximation with artificial neural networks*. M.S. Hungary: Eötvös Loránd University.

Cullinane, K. P. B., Mason, K. J., & Cape, M., 1999a. A comparison of models for forecasting the Baltic freight index: Box-Jenkins revisited. *International journal of maritime economics*, 1(2), pp. 15-39.

Cullinane, K. P. B., Mason, K. J., & Cape, M., 1999b. Forecasting the baltic freight index: Box-Jenkins revisited. In: The National Academies of Sciences Engineering Medicine., World Transport Research: *Selected Proceedings of the 8th World Conference on Transport ResearchWorld Conference on Transport Research Society* (No. Volume 1), Antwerp, Belgium, July 12~17, 1998. Elsevier: Oxford, United Kingdom, pp. 73-86.

Cybenko, G., 1989. Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals and Systems*, 2(4), pp. 303-314.

Elman, J. L., 1990. Finding structure in time. *Cognitive Science*, 14(2), pp. 179-211.

Fadlalla, A., & Lin, C. H., 2001. An analysis of the applications of neural networks in finance. *Informs Journal on Applied Analytics (Interfaces)*, 31(4), pp. 112-122.

Fan, Y. H., Xing, Y. W., & Yang, H. L., 2014. Prediction of Baltic Capesize Freight Index Based on GARCH Model. *In Applied Mechanics and Materials*, 488, pp. 1494-1497.

Gal, Y., & Ghahramani, Z., 2016. A theoretically grounded application of dropout in recurrent neural networks. In: Lee, D. D. et al., Neural Information Processing Systems 2016, *Advances in Neural Information Processing Systems 29 (NIPS 2016)*, pp. 1019-1027.

Geman, H., & Smith, W. O., 2012. Shipping markets and freight rates: an analysis of the Baltic Dry Index. *Journal of Alternative Investments*, 15(1), pp. 98-109.

Gers, F. A., Schmidhuber, J., & Cummins, F., 1999. Learning to forget: Continual prediction with LSTM. In: *1999 Ninth International Conference on Artificial Neural Networks ICANN 99*, Edinburgh, UK, September 7-10, 1999, IEEE: New York City, USA, pp. 850-855.

Guan, F., Peng, Z., Wang, K., Song, X., & Gao, J., 2016. Multi-Step Hybrid Prediction Model Of Baltic Supermax Index Based On Support Vector Machine. *Neural Network World*, 26(3), pp. 219-232.

Guo, J., 2013. *Backpropagation through time*. M.S. Harbin Institute of Technology.

Han, Q., Yan, B., Ning, G., & Yu, B., 2014. Forecasting dry bulk freight index with improved SVM. *Mathematical Problems in Engineering*, 2014, pp. 1-12.

Hochreiter, S., & Schmidhuber, J., 1997. Long short-term memory. *Neural Computation*, 9(8), pp. 1735-1780.

Hochreiter, S., Bengio, Y., Frasconi, P., & Schmidhuber, J., 2001. *Gradient flow in recurrent nets: the difficulty of learning long-term dependencies*. pp. 1-15.

Hornik, K., 1991. Approximation capabilities of multilayer feedforward networks. *Neural Networks*, 4(2), pp. 251-257.

Jordan, M. I., 1997. Serial order: A parallel distributed processing approach. *In Advances in Psychology*, 121, pp. 471-495.

Kavussanos, M. G., & Alizadeh-M, A. H., 2001. Seasonality patterns in dry bulk shipping spot and time charter freight rates. *Transportation Research Part E: Logistics and Transportation Review*, 37(6), pp. 443-467.

Kavussanos, M. G., & Alizadeh-M, A. H., 2002. Seasonality patterns in tanker spot freight rate markets. *Economic Modelling*, 19(5), pp. 747-782.

Kuan, C. M., & White, H., 1994. Artificial neural networks: An econometric perspective. *Econometric Reviews*, 13(1), pp. 1-91.

Leonov, Y., & Nikolov, V., 2012. A wavelet and neural network model for the prediction of dry bulk shipping indices. *Maritime Economics & Logistics*, 14(3), pp. 319-333.

Li, J., & Parsons, M. G., 1997. Forecasting tanker freight rate using neural networks. *Maritime Policy & Management*, 24(1), pp. 9-30.

Lin, F., & Sim, N. C., 2013. Trade, income and the baltic dry index. *European Economic Review*, 59, pp. 1-18.

Lyridis, D. V., Zacharioudakis, P., Mitrou, P., & Mylonas, A., 2004. Forecasting tanker market using artificial neural networks. *Maritime Economics & Logistics*, 6(2), pp. 93-108.

Papailias, F., Thomakos, D. D., & Liu, J., 2017. The Baltic Dry Index: cyclicalities, forecasting and hedging strategies. *Empirical Economics*, 52(1), pp. 255-282.

Saad, E. W., Prokhorov, D. V., & Wunsch, D. C., 1996. Advanced neural network training methods for low false alarm stock trend prediction. In: Neural Networks, 1996., *Proceedings of International Conference on Neural Networks (ICNN'96)*, Washington, DC, USA, June 3-6, 1996, IEEE: New York City, USA, pp. 2021-2026.

Saad, E. W., Prokhorov, D. V., & Wunsch, D. C., 1998. Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks. *IEEE Transactions on Neural Networks*, 9(6), pp. 1456-1470.

Scarsi, R., 2007. The Bulk Shipping Business: Market Cycles and Shipowners' Biases. *Maritime Policy & Management*, 34(6), pp. 577-590.

Signal Trading Group, 2011. revised in 2012. Bakshi, G., Panayotov, G., & Skoulakis, G., *The Baltic Dry Index as a predictor of global stock returns, commodity returns, and global economic activity*, [Online] (Update February 29, 2012) Available at: www.signaltradinggroup.com/wp-content/WhitePapers/Baltic Dry Index as a Predictor.pdf [Accessed December 1, 2018].

Stopford, M. 2013. *Maritime economics*. 3rd Ed. Routledge: London.

Sutskever, I., 2013. *Training recurrent neural networks*. Ph.D. Canada: University of Toronto.

Sutskever, I., Vinyals, O., & Le, Q. V., 2014. Sequence to sequence learning with neural networks. In: Ghahramani, Z. et al., Advances in neural information processing systems, *Neural Information Processing Systems 2014*, pp. 3104-3112.

Thorsen, I.S., 2010. *Dry Bulk Shipping and Business Cycles.* M.S. Norwegian School of Economics and Business Administration.

Γούλας, Λ., 2012. *Forecasting freight rates: evidence from the baltic exchange indices and the IMAREX freight futures.* M.S. Greece: University of Piraeus.

Τσιούμας, Ε., 2016. *Quantitative analysis of the dry bulk freight market, including forecasting and decision making*. Ph.D. Greece: University of Piraeus.

Tsioumas, V., Papadimitriou, S., Smirlis, Y., & Zahran, S. Z., 2017. A Novel Approach to Forecasting the Bulk Freight Market. *The Asian Journal of Shipping and Logistics*, 33(1), pp. 33-41.

United Nations Conference on Trade and Development (UNCTAD), 2016. *Review of Maritime Transport 2016*, Geneva: UNCTAD.

United Nations Conference on Trade and Development (UNCTAD), 2017. *Review of Maritime Transport 2017*, Geneva: UNCTAD.

United Nations Conference on Trade and Development (UNCTAD), 2018. *Review of Maritime Transport 2018*, Geneva: UNCTAD.

Uyar, K., Ilhan, Ü., & İlhan, A., 2016. Long term dry cargo freight rates forecasting by using recurrent fuzzy neural networks. In: Aliev, R.A. et al., Procedia Computer Science, *12th International Conference on Application of Fuzzy Systems and Soft Computing (ICAFS 2016)*, Vienna, Austria, August 29-30, 2016, Elsevier: Oxford, United Kingdom, 102, pp. 642-647.

Vinyals, O., Toshev, A., Bengio, S., & Erhan, D., 2015. Show and tell: A neural image caption generator. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, IEEE: New York City, USA, pp. 3156-3164.

Werbos, P. J., 1990. Backpropagation through time: what it does and how to do it. In: *Proceedings of the IEEE*, IEEE: New York City, USA, 78(10), pp. 1550-1560.

Zeng, Q., & Qu, C., 2014. An approach for Baltic Dry Index analysis based on empirical mode decomposition. *Maritime Policy & Management*, 41(3), pp. 224-240.

Zeng, Q., Qu, C., Ng, A. K., & Zhao, X., 2016. A new approach for Baltic Dry Index forecasting based on empirical mode decomposition and neural networks. *Maritime Economics & Logistics*, 18(2), pp. 192-210.

Zhang, G. P., 2012. *In Handbook of Natural Computing: Neural Networks for Time-series Forecasting.* (pp. 461-477). Springer: Berlin, Germany.

Bibliographies.

한민수, 유성진, 2017. Recurrent Neural Networks를 활용한 Baltic Dry Index (BDI) 예측, 2017년도 한국항해항만학회 추계학술대회.

Allaire, J. J., & Chollet, F., 2018. *keras: R Interface to 'Keras'*. R package version 2.2.0. Available at: https://CRAN.R-project.org/package=keras.

Allaire, J. J., & Tang, Y., 2018. *tensorflow: R Interface to 'TensorFlow'*. R package version 1.9. Available at: https://CRAN.R-project.org/package=tensorflow.

Alphaliner, Alphaliner Monthly Monitor (September 2018), France: Alphaliner.

Chu, C. S. J., 1995. Time-series segmentation: a sliding window approach. *Information Sciences*, 85(1-3), pp. 147-173.

Clarksons Research Services Limited, Shipping Review & Outlook 2018, London: Clarksons Research.

Drewry Shipping Consultants Limited, Shipping Insight 2018, London: Drewry.

Duru, O., & Yoshida, S., 2011. Long term freight market index and inferences. *The Asian Journal of Shipping and Logistics*, 27(3), pp. 405-421.

Grammenos, C., 2013. *The handbook of maritime economics and business*. 2nd Ed. Taylor & Francis: London.

Günther, F., & Fritsch, S., 2010. Neuralnet: Training of neural networks. *The R Journal*, 2(1), pp. 30-38.

Hyndman, R. J., & Athanasopoulos, G., 2018. *Forecasting: principles and practice*. 2nd Ed. OTexts: Melbourne.

Hyndman, R. J., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E., & Yasmeen, F., 2018. *forecast: Forecasting functions for time series and linear models*. R package version 8.4, Available at: http://pkg.robjhyndman.com/forecast.

Jeffrey, B. A., 2018. *ggthemes: Extra Themes, Scales and Geoms for 'ggplot2'*. R package version 4.0.1. Available at: https://CRAN.R-project.org/package=ggthemes.

Luo, B., 2015. *Do the sub-indices of the BDI have better predictability for stock market returns than the BDI?* M.S. Istanbul: Tilburg University.

Oomen, J., 2012. *The Baltic Dry Index: A predictor of stock market returns*. M.S. Istanbul: Tilburg University.

Pástor, Ľ., & Stambaugh, R. F., 2009. Predictive systems: Living with imperfect predictors. *The Journal of Finance*, 64(4), pp. 1583-1628.

Quast, B.A., 2016. *rnn: a Recurrent Neural Network in R*. Available at: http://qua.st/rnn.

R Core Team, 2018. R: A language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria. Available at: https://www.R-project.org/.

RStudio Team, 2015. *RStudio: Integrated Development for R. RStudio, Inc.*, Boston, MA. Available at: http://www.rstudio.com/.

Stefan, F., & Frauke, G., 2016. *neuralnet: Training of Neural Networks*. R package version 1.33. Available at: https://CRAN.R-project.org/package=neuralnet.

Vafaeipour, M., Rahbari, O., Rosen, M. A., Fazelpour, F., & Ansarirad, P., 2014. Application of sliding window technique for prediction of wind velocity time-series. *International Journal of Energy and Environmental Engineering*, 5(2-3), p. 105.

Wickham, H., 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York, 2016. Available at: http://ggplot2.org.

Williams, R. J., & Peng, J., 1990. An efficient gradient-based algorithm for on-line training of recurrent network trajectories. *Neural Computation*, 2(4), pp. 490-501.

Appendix.

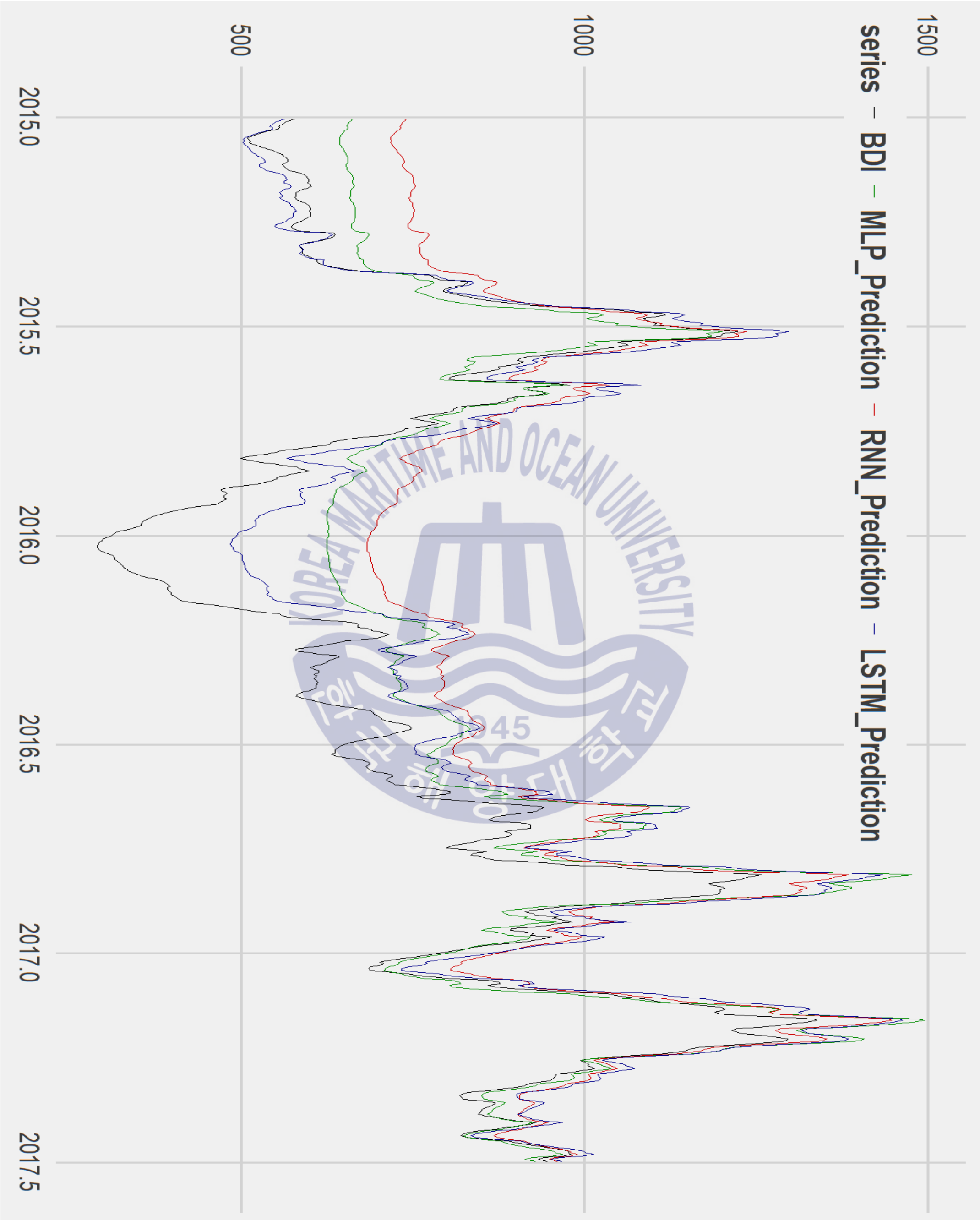

Fig. 24 Over-plotting the results of all ANN models fitting on the test set (enlarged)

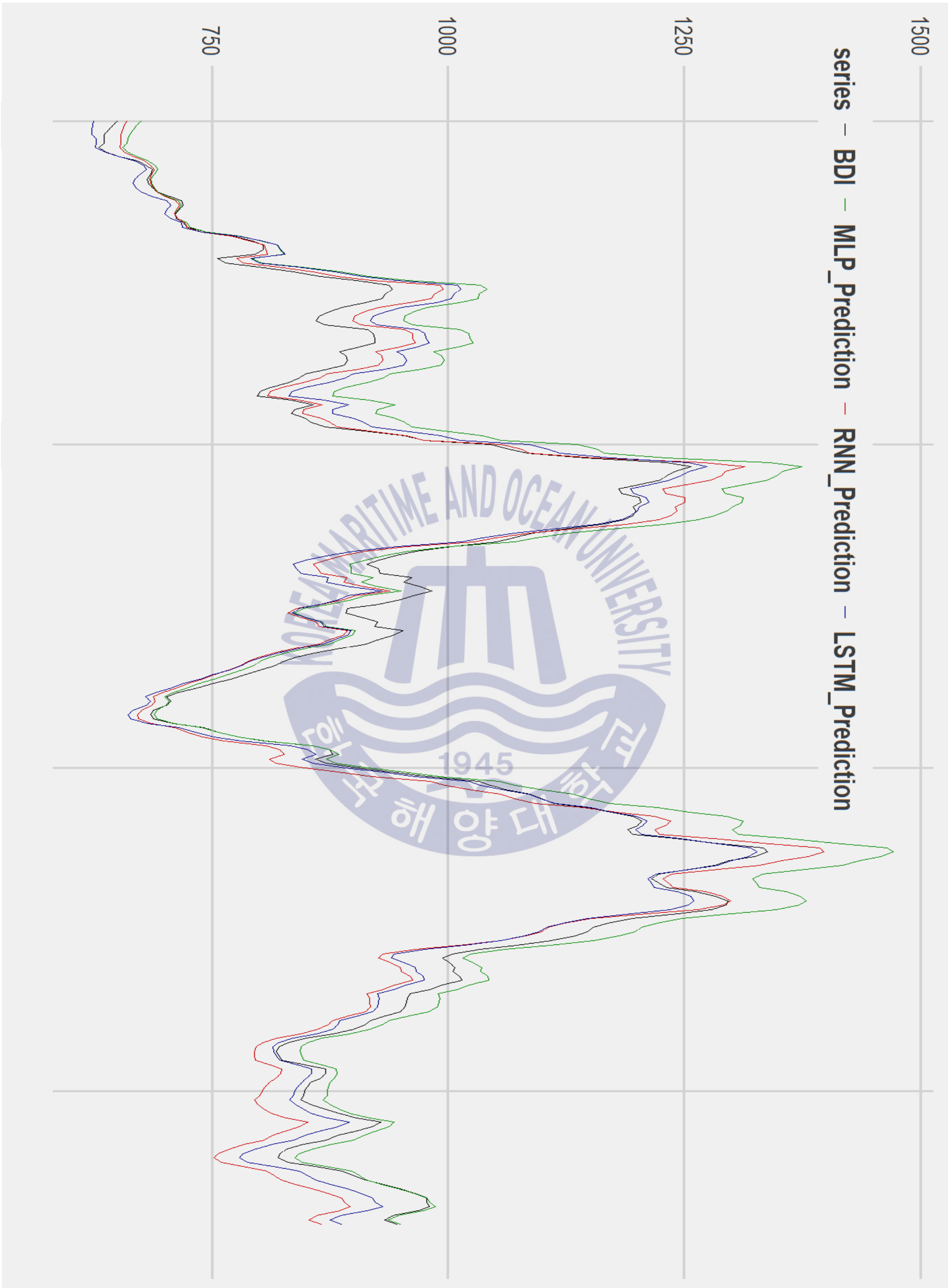

Fig. 25 Over-plotting the prediction results of all ANN models (enlarged)