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Feasibility Study of Adaptive Neuro-Fuzzy Inference System (ANFIS) with Genetic Algorithms (GA) and Particle Swarm Optimizations (PSO) in Predicting Baltic Exchange Dirty Tanker Index (BDTI)

by

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Abstract

OPEC has projected crude oil consumption to reach around 110 million barrels in 2045. This constitutes an increase by 13 million barrels compared with the oil consumption in 2021. Increasing the oil consumption would impact not only the upstream but also the midstream of industry. Consequently, oil tankers which are the most efficient vehicle to transport oil in massive quantity remain the backbone of the world energy chain. Crude oil tankers' freight rate is one of the most interesting issues within the oil and gas industry because it is the one of components in calculating the consumer price of oil products. Several studies have been conducted to determine models for predicting the freight rate using econometrics and stochastics models. Generally, the models face difficulties in predicting the value in the long run due to volatility and uncertainty in the freight rate. This research focuses on a hybrid model of an artificial neural network and fuzzy system which is called Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate the Baltic Dirty Tanker Index (BDTI). ANFIS generally shows good forecasting performance, but the approach has not been applied in BDTI forecasting. This thesis implements three different ANFIS systems which are the original form, ANFIS in combination with a Genetic Algorithm (GA), and ANFIS with Particle Swarm Optimization (PSO). The machine learning component in the original ANFIS form utilizes two algorithms which are Gradient Descent (GD) to adjust nonlinear premise parameters and Recursive Least Square Error (LSE) for setting linear parameters. In the combination model, GA and PSO are utilized to optimize the parameters. The performance of each model is measured by Root Mean Square Error (RMSE), Coefficient of Variation of The Root Mean Squared Error (CVRMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Regarding the simulation results, all of ANFIS models are suitable to forecast BDTI and ANFIS – PSO shows advantages over the other two forms.

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List of Abbreviations

ANFIS - Adaptive Neuro-Fuzzy Inference System

API – American Petroleum Institute

ARCA – Archipelago (in New York Stock Exchange)

ARIMA - Autoregressive Integrated Moving Average

ARMA- – Autoregressive Moving Average

CRB - Commodity Research Bureau

CVRMSE - Coefficient of the Variation of the Root Mean Square Error

GA – Genetic Algorithms

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

GDP – Gross Domestic Product

IMO – International Maritime Organization

LIBOR - London Interbank Offer Rate

MAE – Mean Absolute Error

MAPE – Mean Absolute Percentage Error

MARPOL – Marine Polution

NYSE – New York Stock Exchange

OPEC – Organization of the Petroleum Exporting Countries

PSO – Particle Swarm Optimization

RMSE – Root Mean Square Error

SSECI – Shanghai Stock Exchange Composite Index

ULCC – Ultra Large Crude Carrier

VAR – Vector Auto Regression

VECM - Vector Error Correction Model

VLCC - Very large crude carrier

WTI – West Texas Intermediate

Chapter 1. **Introduction**

This chapter discusses the conditions that inspire to conduct of this research and also the development of related research. Those matters are included in the background section. The section also consists of the main research question and its sub-questions. The second part of chapter one explains the research design and methodology. The steps for the simulation are briefly elaborated in this part. Lastly, the structure of the report is accounted for in the last part of the first chapter.

1.1. Background

OPEC (Organization of the Petroleum Exporting Countries) has projected crude oil consumption to reach around 110 million barrels in 2045. This constitutes an increase by 13 million barrels compared with the oil consumption in 2021. It is also predicted to maintain its position as the largest proposition (29 %) in the energy mix in 2045 (OPEC, 2022). Increasing the oil consumption would impact not only the upstream but also the midstream of the oil and gas industry. Consequently, oil tankers which are the most efficient vehicle to transport oil in massive quantity remain the backbone of the world energy chain.

Crude oil tankers' freight rate is one of the most interesting issues within the shipping industry because the freight rate is one of the most important factors in determining shipping economics. Several studies have been conducted to determine models for predicting the freight rate using econometrics and stochastic models such as ARIMAX for predicting crude oil tanker freight rate (Christodoulopoulos, 2020), VAR, and VECM to estimate time charter rate for various tanker vessel sizes (Diakodimitris, 2019). Based on several studies, the models, especially ARIMA, face difficulties in predicting the value in the long run due to volatility and uncertainty in the freight rate. Meanwhile, machine learning has been widely used to predict many parameters in the context of business, for example, customer satisfaction forecast for new products using a hybrid system of ANFIS and PSO (Jiang *et al.*, 2012). Regarding the machine learning application on the freight rate prediction, a study was conducted to compare WNN and ARIMA to estimate BDTI as the most important index to represent crude oil freight rate. The research showed that WNN is superior to ARIMA in long-term prediction while in the short term, they do not have a significant difference in performance (Fan *et al.*, 2013).

Mathematically, BDTI is calculated based on average rates in the main 19 routes with different weighting factors. ANFIS generally shows good forecasting performance in the maritime industry such as a near-miss assessment during tanker operation (Zhou *et al.*, 2019), but the approach has not been applied in freight rate forecasting. While no model could forecast accurately, the predictions are needed to determine business plans and strategies to face uncertainties in the future.

1.2. Objective and Research Questions

The main question and sub-questions for this research are as follows.

Main Question :

How accurate of ANFIS to predict the Baltic Dirty Tanker Index?

Sub-questions :

1. What are the factors that affect the Baltic Dirty Tanker Index?
2. Which are the most optimum parameters for ANFIS original model that could be used to forecast Baltic Dirty Tanker Index using the given inputs?
3. How is the performance of ANFIS models after it is optimized by Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)?

1.3. Research Design and Methodology

This research focuses on a hybrid model of an artificial neural network and fuzzy system which is called Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate BDTI. In this research, we also compare three different ANFIS models which are the original ANFIS, ANFIS – GA, and ANFIS - PSO. The last two systems use GA and PSO to optimize the model resulting from ANFIS. Initially, a statistical analysis is conducted to find a correlation between BDTI and several candidate parameters from the literature. The parameters that have the biggest three correlation coefficients would be considered as the inputs of the system. The data are taken from January 2008 to December 2019.

Once the input selection step is done, the data are clustered by the Subtractive clustering method to generate the initial membership function in ANFIS to reduce computational time and rules in the function (Joelianto *et al.*, 2013). In the learning process, the original ANFIS form utilizes two algorithms which are Gradient Descent (GD) to adjust nonlinear premise parameters and Recursive Least Square Error (LSE) for setting linear parameters. In the combination model, GA and PSO are utilized to optimize ANFIS's original parameters to get optimum results. After the learning process is finished, the models are validated with certain data. Next, the performance of each model is measured by Root Mean Square Error (RMSE), Coefficient of Variation of The Root Mean Squared Error (CVRMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAEP).

1.4. Structure of Thesis

This thesis is divided into six chapters which are the Introduction for Chapter 1, the literature review for both Chapters 2 and 3, the methodology in Chapter 4, and the results as well as the conclusion in Chapters 5 and 6 respectively. The main difference between chapters 2 and 3 is the topic discussion. While Chapter 2 focuses on the crude oil tanker market, Chapter 3 discusses machine learning as the main method in this research.

Specifically, The second chapter provides knowledge of shipping aspects in the research including history, characteristics, and the most influential factors in the crude oil tankers market. The definition, internal, and external determinants of BDTI are the main focus of this chapter since they are the inputs and output of the research. On the other hand, Chapter 3 presents some machine learning algorithms with an emphasis on Subtractive Clustering, ANN, Fuzzy Systems, ANFIS, GA, and PSO including their definition, learning methods, and structure as they are used in the research. Several perspectives such as the previous research results are considered to determine the used methods in the research. The explanation of subtractive clustering to create initial membership functions for ANFIS and how ANFIS combined with GA and PSO are also provided in this chapter.

Next, The fourth chapter consists of three parts which are data analysis, modeling prediction system, and model evaluation. In the data analysis part, the chapter explains statistical tests to calculate the correlation coefficient of inputs to choose the most significant input parameters and some essential statistics parameters in this thesis are also explained in this part. Meanwhile, the steps and their detailed description which are started by subtractive clustering and ended by the optimal ANFIS models are included in the modeling part. The last section of the fourth chapter elaborates on the definition of the optimal model used in this research including the metrics explanation provided in this chapter as well. Then, Chapter 5 emphasizes the results and their analysis. Statistic analysis, highlight of trials in each model, and model comparison are the essential content of the fifth chapter. Some graphs and tables are also used to figure out the comparisons of results and support the explanation in this chapter.

Lastly, The conclusions and suggestions for future research are stated in Chapter 6. As future works should take the limitations of this research into account, the ones are presented in the suggestion part. Besides them, the questions and sub-questions are answered in the second part of this chapter.

Chapter 2. **Crude Oil Tanker Market**

2.1. History

Oil, one of the most valuable commodities since about a century ago, was started commercially produced in 1859 at Titusville, Pennsylvania. Two years later, the oil cargo was transported by 'Elizabeth Watts' vessel using barrels for London. For some reasons, such as its size and difficulty to handle, the barrels were replaced by wooden cases, which became the reference for the cargo unit. In 1886, the era of bulk oil transport was begun when a containment vessel with the name of Gluckauf, was launched for the German-American Petroleum Company. In only 4 years since the launch, the fleet number in the Atlantic increased by 750 %, from 12 tankers in 1886 to 90 tankers in 1891 (Stopford, 2009).

In between 1950s and 1960s, the oil transportation system was controlled by the big oil companies and it also became a core business for the oil companies. During the decades, the size of oil tankers increased significantly from 17,000 dwt in 1950 to the first VLCC and the first ULCC in 1966 and 1976 respectively due to economics of scale. An example of this was the roundtrip between Rotterdam and Kuwait using a 200,000 dwt vessel could save the cost by 34 % compared with sailing with an 80,000 dwt vessel. Also, transport planning played an important role in order to optimize the tankers which were only slightly below the theoretical optimum. Another principle that was commonly used by the oil companies at this time was the subcontracting strategy. To avoid the higher companies' fixed costs, they subcontracted the fleet to independents, for instance, Greeks and Norwegians managed the Atlantic Market while Hongkong operated the Japan market. Spreading the risk is another reason why the oil companies subcontracted tankers to the independents in this era.

The transportation business changed in the 1970s when oil transport was not a business core for many oil and gas companies due to the oil trade decrease. This condition was figured by the oil tankers' ownership shifting from the oil and gas companies with time charter to independent tanker fleet. The end of the coal transition, maturity in main energy markets regions such as Europe and Japan, and advancing technologies in efficiency had important roles in reducing oil consumption and then the oil and gas industries entered a volatile era. In the 1980s, the oil price touched US$ 11 / barrel and stayed in a range of US$ 11 – 25 / barrel until the end of the 1990s.

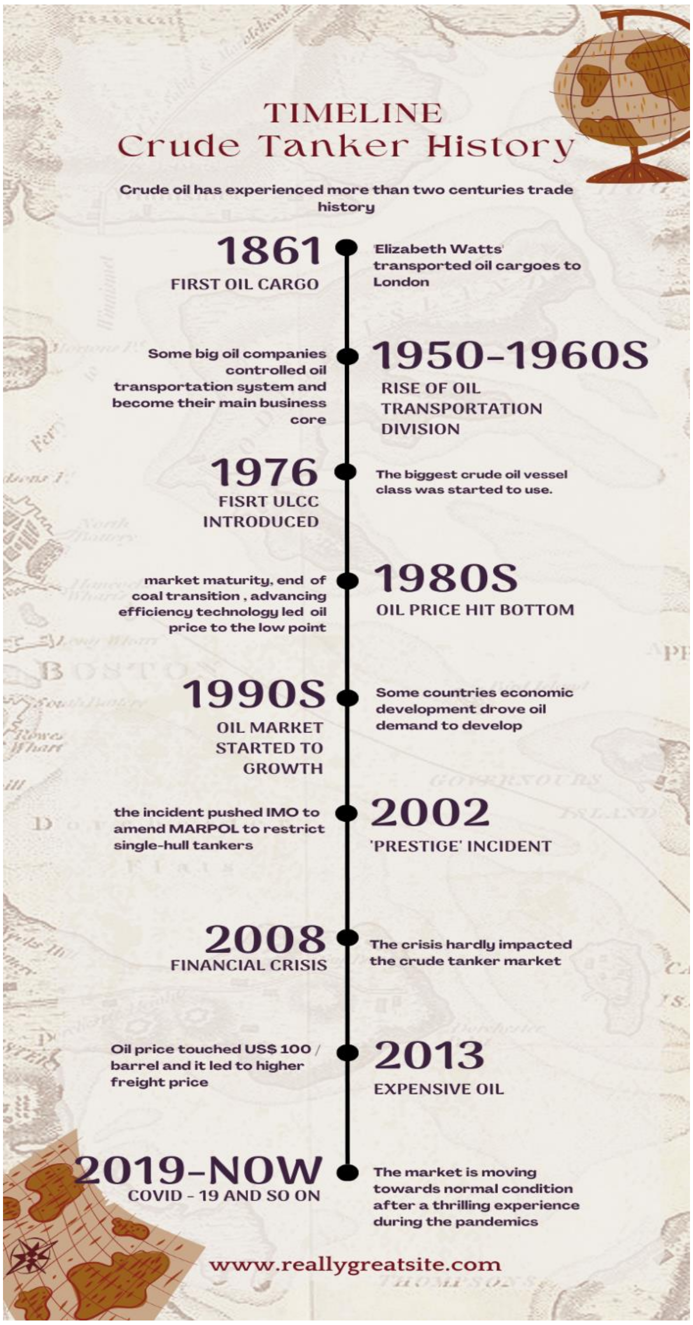

Figure 2-1 Crude Oil Tanker Market History Timeline

The 1990s also became a turning point for energy trading due to some countries' economic development. The Asian economic crisis in 1997 impacted hardly to the international tanker market but the market revived with the rise of oil prices. The main factor that is oil became one of the backbones of economics, military activities, and political bargains among the countries at the beginning of the third millennium. Unexpectedly, the incident of "Prestige" in 2002 pushed IMO to amend MARPOL to restrict single-hull tankers and it caused a disruption in the tanker market in terms of its capacity (International Maritime Organization, 2019).

The tanker market enjoyed positive growth between 2003 and 2008 and then it dropped in the period of between 2009 and 2012 as the impact of the financial crisis. In the following year, the high oil price was the one of significant factors that made the freight rate rose and then the market was more in a steady state from 2013 to 2019 compared with the previous years. The beginning of Covid-19 in 2019 reduced economic activities and it hit almost all industrial sectors, especially the shipping and energy industry. As a consequence, Baltic Dry Tanker Index touched the lowest limit at the beginning of 2021 but the surge of demand during 2021 made many shipping companies get much profit. In 2022, the crude tanker market experienced higher prices due to geopolitical tension between Russia and Ukraine. Currently, the tanker market is moving toward its normal condition, and some of the big energy companies develop the oil transport division to take full control upstream, midstream, and downstream sides of the industry in order to overcome the market's uncertainty. **Figure 2-1** summarizes the crude market history.

2.2. Characteristics and The Most Important Influencing Factors

Several main characteristics are highlighted in the oil tanker market. The first significant characteristic is that the market is cyclical. In most cases, oil prices have a correlation with oil tanker freight rate (Pouliasis and Bentsos, 2023) while the main drivers of oil prices are several political and economic events such as the financial crisis and middle east tension since the world oil supply is dominated by certain countries, especially some Arab countries. Also, OPEC+ policies have a great influence on determining the oil price. The organization has the main objective of maintaining oil prices at profitable levels by managing oil supply numbers. All of the events and policies make oil prices move in a volatile as well as uncertain level and it impacts significantly to oil tanker freight rate.

The oil tanker sector is characterized by the presence of long-term length contracts as its second notable feature. Contracts are frequently employed as a means of remunerating for the cyclical nature and uncertainties inherent in the sector. Moreover, the implementation of long-term contracts has the potential to ensure a stable and consistent cash flow for oil tanker firms. The duration of contracts can exhibit significant variation, ranging from a few months to many years. This variability is contingent upon a multitude of factors, including the size of the vessel, the volume of oil being delivered, and the specific routes involved. Long-term contracts in the oil production industry serve to guarantee the timely transfer of oil to consumers within a certain timeframe. Contracts typically include the delineation of responsibilities for each party involved.

Regarding environmental issues, some regulations related to oil tankers have been implemented. In 1992, IMO announced that every tanker that was ordered after 6 July 1993 must be double-hull or have a design with IMO approval, and then IMO started to obligate existing single-hull tankers to convert to double-hull in 1995. However, the complete implementation of this policy was hindered due to the shipyard's constrained capacity, which would have resulted in significant disruptions within the industry. The incident of 'Erika' off the coast of France in December 1999 motivated IMO members to speed up the transition to double-hull tankers. As a result, IMO members agreed to amend MARPOL in 2001 which consisted of a stricter timeline for the double-hull transition (International Maritime Organization, 2019). Some countries and regions also implement regulations related to the transition such as the EU which published Regulation (EU) No 530/2012. Undoubtedly, the usage of double-hull tankers reduces the risk of oil spills in most cases.

In recent times, some major oil corporations have undertaken the establishment of oil transportation departments. This strategic move by the firms may potentially pose challenges for independent owners of tankers in the foreseeable future. Moreover, the market is mostly controlled by larger tanker types that necessitate a substantial initial capital outlay. However, despite the projected growth in oil trade volume, the prominent independent tanker owners are expected to sustain their market segment. Consequently, the prevailing market structure would exhibit characteristics of an oligopoly, as the tanker market is predominantly controlled by major oil firms and prominent independent ship owners.

2.3. Baltic Dirty Tanker Index (BDTI)

BDTI or Baltic Dry Tanker Index is an index that is produced by Baltic Exchange, a prominent maritime data provider. The main purpose of BDTI is to give a reference to market players such as shipowners, charterers, and investors for evaluating past and current freight rates in the crude oil tanker industry. The index could be used to forecast the future market and as a basis for several companies and investors to determine their business and investment strategies in certain cases.

The index is expressed in a numerical value with a unit of USD/day. In the simplest way, the increasing index means the higher average freight rate and demand or excessive vessel supply. On the other hand, the decline in index figures that the market is in a weaker condition. The index is only focused on crude oil tanker freight rates with a focus on the following types of tankers.

VLCC

VLCC or Very Large Crude Carrier is the one of supertanker types with a size over 200,000 dwt. This type of vessel is usually used to carry crude oil over long distances. The amount of crude oil that can be transported by the vessel is up to 2 million barrels. The VLCC routes from the Middle East Gulf to both the US Gulf (TD1) and China (TD3C) are the two components for BDTI calculations.

Suezmax

Suezmax or a type of crude oil tanker that is designed to pass the Suez Canal. the dwt of tanker is between 120,000 and 249,999 and its draft is approximately 11.6 meters. As most oil tankers from the Middle East go through the canal to Europe, this tanker type is commonly used in the regions. Besides them, the tanker is also used in West Africa and the Black Sea Area such as Nigeria and Russia. The codes TD6 (Black Sea – Mediterranean) and TD20 (West Africa – UK Continent) are Suezmax sailings in BDTI calculation factors.

Aframax

This kind of tanker has a capacity smaller than 120,000 dwt but more than 80,000 dwt. The term ‘AFRA’ actually comes from Average Freight Rate Assessment, Shell Oil’s standard for its tanker rate system. Because of the vessel’s suitable size, it is commonly used to transport oil in small – medium distances and to small harbors such as the ones in non-OPEC countries. The disadvantage of this vessel type is that it can not pass the original Panama size due to its breadth size. This type of Vessel has the biggest share in the BDTI calculation since it occupies 6 of 13 routes in BDTI components which are North Sea – EU Continent (TD7), Kuwait – Singapore (TD8), Caribbean – US Gulf (TD9), South East Asia – East Coast Australia (TD14), Baltic – UK Continents (TD17), and Cross Mediterranean (TD19).

In terms of the index calculation method, the panelists which are some shipbrokers input their estimation of average daily freight rate (AV_i) for the different crude oil tankers’ capacity in several routes which are figured in **Table 2-1**. The routes are selected regarding three main considerations that are trade volume, transparency, and standard terms (The Baltic Exchange, 20??). The trade volume criteria avoid the routes which have seasonal routes such as the Great Lakes in North America. A consistent and substantial volume of trade on routes and other routes related to them is the most considerable factor to determine the routes to be indexed. Transparency refers to reliable reports availability and this criterion also considers, if possible, the number of interest. The smaller number of interest leads the routes to be less considerable. The last criterion is standard terms which means that routes using standard terms will be prioritized to be included as the basis of BDTI calculation. Once the routes have been established, the freight rates are multiplied by the weighting factors (WF_i) and the total of the multiplication is the index (Baltic Exchange, 2023). **Formula 2.1** is used to determine the index.

(2.1) $$BDTI = 8.596354178 \,.\, \sum_i^n (AVi \,.\, WF_i)$$

Table 2-1 BDTI Components in June 2023 (Baltic Exchange, 2023)

No (AV_i)	Route	Weighing Factor (WF_i)
TD1	Middle East Gulf – US Gulf	0.07692
TD2	Middle East Gulf – Singapore	0.07692
TD3C	Middle East Gulf – China	0.07692
TD6	Black Sea to the Mediterranean	0.07692
TD7	North Sea to EU Continent	0.07692
TD8	Kuwait - Singapore (Crude/DPP heat 135F)	0.07692
TD9	Caribbean - US Gulf	0.07692
TD14	South East Asia - east coast Australia	0.07692
TD15	West Africa – China	0.07692
TD17	Baltic – UK Continent	0.07693
TD18	Baltic - UK-Continent	0.07693
TD19	Cross Mediterranean	0.07693
TD20	West Africa - UK-Continent	0.07693

Factors Influencing BDTI

Fan et al divided BDTI internal determinants into three main factors which are cash flow (cost and revenue), vessel specification, and route and haul in 2013. Each internal determinant depends on some external factors that are used to select model inputs in this thesis as figured in **Table 2-2**. This research also considers the influencing factors for the other Baltic Indices as input candidates for the models.

Table 2-2 Factors Influencing BDTI

Internal Determinants	External Determinants	Model Candidate Inputs	Proposed by
Route and Haul	Global Oil Supply	NYSE ARCA Oil Index	(Fan *et al.*, 2013)
	Global Oil Demand		
Cost and Revenue	Oil Price	Brent Crude Oil Price	(Fan *et al.*, 2013)
	World Economic Condition	Shanghai Stock Exchange Composite Index	(Pepur, Peronja and Laća, 2022)
		S & P 500 Volatility	(Fan *et al.*, 2013 & Pepur *et al.*, 2022)
		Gold	(Pepur *et al.*, 2022)
		CRB Index	(Pepur *et al.*, 2022)
Vessel Specification	Shipping Capacity	Dow Jones Marine Transportation Total Stock Market Index	New Proposed
		MSCI World Marine Index	New Proposed

Route and Haul

The routes for crude oil tankers are influenced by external determinants of global oil supply and demand, as these factors determine the locations of oil producers and customers. An increase in the volume of oil traffic between two places enhances the significance of the route connecting them, perhaps warranting its inclusion as a factor in the calculation of the Baltic Dirty Tanker Index (BDTI).

At now, the global oil-producing landscape is characterized by the dominance of not only Middle Eastern nations but also other significant players such as Russia and the United States. China and India have emerged as significant contributors to the global demand for energy, mostly due to their substantial levels of energy consumption. Consequently, the establishment of more routes would ensue. If the trade volume within these routes reaches a substantial level, the route would be deemed eligible for inclusion in the BDTI routes list.

This thesis investigates the NYSE ARCA Oil Index as a means to analyze and depict the dynamics of oil supply and demand. The index formerly referred to as the Amex Oil Index was officially introduced on August 27, 1984. The calculation is determined through the use of the price-weighted principle, or alternatively, it is contingent upon the variations in the total price of its constituent components. Several prominent oil corporations, including Total S.A, Shell, and ExxonMobil, have been included as constituents of this index. The index presented above offers a practical means of assessing the success of the oil and gas industry, which is contingent upon the dynamics of oil supply and demand.

Cash Flow (Cost and Revenue)

World economic conditions and oil prices are the most considered external determinants for cash flow. Higher oil price results in the fuel cost of shipping rising and as a consequence in operation activities, it would reduce the vessel operators' profit. Besides that, oil prices could affect the demand for oil transportation while the correlation between oil prices and crude oil tanker freight rates is non-linear (Euronav, 2017). West Texas Intermediate (WTI) and Brent Crude are two oil types that are commonly used as oil price references. Both of them have high API numbers since they could be grouped as light oil. In terms of extraction locations, WTI is produced from several regions in the US, for instance, Texas and North Dakota while Brent crude oil is exploited from the North Sea Region including Forties and Brent. This thesis uses Brent Crude Oil price as one of the candidate model inputs because more than 60 % of crude oil contracts in the world use Brent crude oil price as their benchmark.

Currently, global economics is dominated by two major countries, the US and China. With its huge population and market, China could drive the economy, especially on the demand side. Regarding that condition, the thesis considers Shanghai Stock Exchange Composite Index (SSECI) as the one of model inputs because the index is a prominent indicator for measuring Chinese economic condition. On the other hand, S&P 500 is also examined in this thesis to represent US economics which has the biggest GDP in the world in 2021. This index presents a weighted average stock price from the 500 biggest US companies.

Global economics could not be depicted only by some stock indices but also by commodity prices. Traditionally, gold is considered the safest commodity to preserve wealth, especially in an uncertain economic condition. In other words, a higher gold price indicates less economic health. Another indicator related to commodities that need to be examined is the CRB index for commodities. The index is formed by 19 commodities which are dominated by agricultural products (41 %) and energy products (39%). The remaining one-fifth is occupied by industrial metals and precious metals with a percentage of 13% and 7% in turn (Refinitiv, 2023).

Vessel Specification

Several indicators are usually used to examine the capacity of the shipping industry which have a strong relationship with the availability of vessel specification. In terms of the tanker market, a new order could figure optimism for the industry while a ship scrapping means a reduction of the industry's capacity by a certain amount. Actually, there are several reasons why companies or shipowners book a vessel such as to regenerate their fleet and reduce their operational expenditures. On the other hand, ship scrapping activities are conducted because the ship has achieved its age and also, an economical reason usually motivates the shipowner to remove their fleet. As the industry’s capacity is one of the freight main drivers, scrapping and ordering are the key activities to control the freight as well.

Some indices could also indicate the capacity of the shipping industry, such as the MSCI World Transportation Index (Fan *et al.*, 2013). Nonetheless, the index consists of only 5.46 % for the sea transportation portion and it is not sufficient to represent the tanker industry (MSCI, 2023). Alternatively, This thesis proposes the Dow Jones Marine Transportation Total Stock Market Index and MSCI World Marine Index. The first index is designed to cover on-water transportation companies such as container shipping while the second one represents the middle and large marine segments in 23 developed countries.

2.4. Previous Related Studies

This section describes several previous related studies including the ones which use both machine learning and mathematical models. In 2013, Fan et al research on the feasibility of a wavelet neural network (WNN) to predict the Baltic Dirty Tanker Index is the main basis for determining the internal and external determinants in this thesis. This research used Amex Oil Index, Brent Crude Oil Price, Volatility S&P 500, S&P Global 1200, Dow Jones, and MSCIAC World Transportation as WNN inputs.

Pepur et al in 2022 examined several prominent indices in the global market in terms of their correlation with the Baltic Dry Index such as gold price, CRB index, 10-year bond yield, and

Shanghai Stock Exchange Composite Index (SSECI) to consider China economics. The result was that S&P 500 and SSECI had a positive correlation with BDI whereas Gold Prices and WTI Crude Oil resulted in a negative impact on the index. The data timeframe of this research is longer than the previous paper.

Wang in 2015 expressed the correlation between some inputs and Baltic Dirty Index using a linear regression model. This paper chose the best four parameters regarding their correlation coefficients. Initially, the paper investigated supply factors (tanker fleet development, tanker demolition, tanker delivery, new building tanker price index, and second-hand tanker price) and demand factors (Brent oil price, global oil production, and S&P 500). At the end of the research, Brent Oil Prices, Tanker Fleet Development, and Global Oil Production are selected as the equation inputs.

The other significant research was conducted by Diakodimitris in 2019 and Christodoulopoulos in 2020 for crude oil freight rate prediction. The first research by Diakodimitris was approached using ARIMA, Box – Jenkins, ARMA–GARCH, VAR, and VECM models for Panamax, Aframax, Suezmax, VLCC, and ULCC. The results were that ARIMA was superior to the other methods. However, the results had high errors based on the MAPE calculation.

In 2020, the research was continued by Christodoulopoulos in order to reduce errors. In later research, He utilized an econometric ARIMA model and consider to add exogenous variables. At the beginning of the research, twelve exogenous variables were investigated but only four variables could improve the ability of the model to predict which are oil price, oil production, LIBOR, and aluminum. Furthermore, only oil price could be suitable with all types of vessels while the most improved model was shown by the model where Oil price acted as the exogenous variable for the Panamax.

Chapter 3. **Machine Learning**

Machine learning is a subfield of artificial intelligence that focuses on the development of algorithms and models that enable computers to make predictions based on acquired knowledge. In this scenario, the computer assimilates the data and utilizes them as the foundation for constructing a model capable of generating predictions. The data undergo analysis by a computer in order to identify patterns, which are subsequently utilized to enhance the machine's performance through iterative processes.

Machine learning can be broadly categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. In the context of supervised learning, the computer acquires knowledge by utilizing labeled input data and subsequently associating them with their respective output values for analysis. Conversely, the computer acquires knowledge from the data and autonomously identifies data patterns through specific algorithms employed in unsupervised learning techniques. The final category of machine learning is reinforcement learning, which involves using an agent to interact with an environment by applying punishments for undesired behavior and rewards for desired behavior to get an ideal solution.

The thesis employs a combination of supervised and unsupervised learning techniques. Subtractive clustering, an unsupervised learning method, serves as the foundation for the development of fuzzy membership functions. Genetic algorithms and particle swarm optimization are additional unsupervised learning approaches that are employed for the purpose of optimizing the ANFIS system. One perspective to consider is that the artificial neural network, which serves as the primary constituent of the Adaptive Neuro-Fuzzy Inference System (ANFIS), is categorized under the supervised learning domain.

3.1. Subtractive Clustering

Clustering is an analytical technique employed to categorize data based on shared characteristics within each respective group and it has a significant portion in machine learning methods in both preprocessing and processing phases. Higher similarities in one group and lower ones among groups are good indicators for the clustering process. The clustering is commonly used in several fields such as marketing (especially for customer segmentation), image processing in the medical subject as well as social network analysis. The clustering process is classified into two big groups which are hard and soft clustering. In soft clustering, each data could be included in more than one group with different membership degrees. This is different from hard clustering where each data is only permitted to become a member of one group.

Subtractive clustering which is the one of hard clustering algorithms uses actual data as the center point. It is different from most clustering methods which use grid points as their center. This center point selection sometimes leads to inaccuracy when the center point comes from the grid point instead of the actual data. Nevertheless, subtractive clustering could provide a good approximation through a reliable and efficient calculation. The number of rules that are generated by this method depends on the input parameters such as accept and reject ratios. The relationship between the ratios and the rules is reversed. Regarding the advantages and disadvantages of the algorithm, the users should manage the trade-off between accuracy and calculation complexity.

In general, subtractive clustering involves 7 different steps to get the final center points. Input data and set parameter values are the first two steps that shall be conducted. The parameters are radius, squash factor, accept ratio, and reject ratio. After finishing setting the parameters, the data is normalized in order to equal their scale without removing the original information. Once the normalization is done, the center point of clusters is initialized and then they are compared with each data point by calculating the potential from each data. The selection process of new cluster centers is stopped once the remaining potential of all data points below the first center point. A detailed explanation of the process is as follows (Chiu, 1994 & Astari, 2018).

Step 1 : enter a set of data to be clustered

X_{ij}, i = 1,2,3,4,…n; j = 1,2,3,4,…m

n = the data number

m = the data type

Step 2 : Set the following parameters' value

- rj = radius parameter
- η = squash factor
- ε^* = accept ratio
- ε = reject ratio
- X_{min} = minimum data for normalization
- X_{max} = maximum data for normalization

Step 3 : Normalization

Each data is normalized using **Equation 3.1**

$$X_{ij}^{Norm} = \frac{X_{ij} - X_{minj}}{X_{maxj} - X_{minj}} \quad (3.1)$$

i = 1,2,3,4,…n ; j = 1,2,3,4,…m

Step 4 : Each data potential calculation

This step is repeated from i = 1 to i = n

If m = 1, use **Equation 3.2**

(3.2) $$P_i = \sum_{i=1}^{n} e^{-4\left\|\frac{x_i - x_k}{r_a}\right\|^2}$$

i = 1,2,3,4,…,n ; k = 1,2,3,..,n; i ≠ k

If m > 1, use **Equation 3.3**

(3.3) $$P_i = \sum_{i=1}^{n} e^{-4\left\|\sum_{j=1}^{m}\frac{x_i^j - x_k^j}{r_b}\right\|^2}$$

i = 1,2,3,4,…,n ; j = 1,2,3,4,..,n; i ≠ j

Step 5 : Find data with the highest potential value

M = max [P_i |i = 1,2,3,4,…,n]

h = i, in order for, D_i = M

Step 6 : The subsequent cluster center is selected based on the following conditions.

If $P_i > M\varepsilon^*, X_k^j$ is accepted as the next cluster center and move to the next step

If $P_i < M\varepsilon, X_k^j$ is rejected as the next cluster center and the process is stopped

If $\varepsilon \le \frac{P_i}{M} \le \varepsilon^*$, X_k^j should be checked whether the point meets the following condition (**Equation 3.4**) or not.

(3.4) $$If\ \frac{d_{min}}{r_a} + \frac{P_i}{M} \ge 1$$

X_k^j is selected to be the next cluster center and continue to step 7

In case X_k^j could not fulfill Equation 3.4, the point is rejected and P_i becomes 0. Next, check other points that have higher P_i and this step is repeated.

Step 7 : Denormalization

The normalized point that becomes cluster centers (X_k^j) is returned to the actual value using **Equation 3.5**

(3.5) $$X_k^j\ (actual\ value) = X_k^j\ (\text{Xmax} - \text{Xmin}) + \text{Xmin}$$

To achieve optimum results, the users should adjust some parameters when they are using subtractive clustering. The parameters are radius parameter (r_a and r_b), accept ratio (ε^*), reject ratio (ε), and squash factor (η). The radius parameter measures a data point's potential to the other data. A higher number in this parameter would result in a smaller cluster number with more members. Otherwise, the smaller number of radius parameter would reduce the number of members but a higher cluster number. The parameter also determines the neighboring data influence on a data point in order to define its potential. The first radius (r_a) is used in the first data type (m = 1) while the other determines the potential data in other data types (m > 1). Practically, rb value is 1.5 times (Chiu, 1994) or 1.25 times (Chiu, 1997) of r_a value. According to Chiu's research in 1997, the optimal range for the value of r_a is typically between 0.2 and 0.5. However, Hammouda and Karray in 2000 demonstrated that a value of r within the range of 0.4 to 0.7 is considered sufficient.

The acceptance ratio imposes a constraint on the selection of data members as cluster centers. A data point would be classified as a cluster center if its data potential exceeds the specified threshold. A decrease in the acceptance ratio would result in an increase in the number of potential candidates for cluster centers. In the context of data clustering, the reject ratio serves as a critical constraint on the ability of the data to function as a cluster center. If the potential of the data falls below this ratio, they cannot be considered cluster centers. In other terms, a greater rejection ratio indicates a more stringent screening process for data members. Another important metric to consider is the squash factor, which is represented as a positive scalar. The variable r is employed to ascertain the extent of the effect exerted by cluster centers. A decrease in the value of this component diminishes the likelihood that outlier points will be classified as part of a cluster. The aforementioned circumstance often results in the formation of a greater number of smaller data clusters.

Clustering, especially the subtractive clustering technique, is a widely employed method for rule generation in the field of fuzzy logic. Subtractive clustering has the potential to aid in the identification of antecedent components of rules through the process of mapping clusters onto the input domain. Moreover, the membership function of each data is defined as the distance between the datum and the center of the cluster. Subtractive clustering has been employed as a fundamental approach in various academic disciplines, including control systems (Joelianto *et al.*, 2013) and psychology (Martínez *et al.*, 2013), to generate fuzzy rules. Furthermore, several comparison studies have been undertaken to compare subtractive clustering with other clustering algorithms, such as C-means. For instance, Astari in 2018 and Bataineh in 2011 found that subtractive clustering outperformed C-means in these investigations.

3.2. Adaptive Neuro Fuzzy Inference System

ANFIS or Adaptive Neuro Fuzzy Inference System which is initially developed by Jang in 1993 is a hybrid system that combines an artificial neural network and fuzzy logic system. It provides a versatile technique to address real-world problems that require both the interpretability of fuzzy logic and the adaptability of neural networks. The system is designed to approximate and optimize intricate nonlinear functions by the automatic adjustment of its parameters, which is informed by input-output data pairs. The proposed model utilizes a configuration of interconnected nodes, whereby each node represents a fuzzy if-then rule. This design enables the model to capture intricate connections between input variables and output variables effectively. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is highly suitable for tasks including function approximation, system modeling, and pattern recognition.

Fuzzy Logic System

The one of fuzzy logic objectives is solving non-binary pattern problems and it was introduced by Zadeh in 1965. The logic is inspired by people's ability to solve non-numerical problems and It uses probability concepts to define the set of data. Fuzzy logic is a computational framework that expands upon traditional binary (crisp) logic in order to effectively manage situations including uncertainty and imprecision. The concept being discussed introduces the notion of degrees of truth, also known as membership degrees, which exist between the binary values of true and false. The membership degree assignment process involves membership functions that have several forms such as including triangular, trapezoidal, Gaussian, and sigmoidal functions to represent how the membership degree is given to each data input.

This allows for the incorporation of subtle transitions and facilitates more flexible reasoning. Fuzzy logic encompasses the utilization of fuzzy sets and rules to describe variables and assertions, hence facilitating a representation of information and decision-making processes that closely resemble human reasoning. The rules generally have two parts which are antecedents and consequences. The antecedent side represents inputs that are based on fuzzy proposition while the consequents consist of conditions to determine the outputs. Moreover, the term rule bases refer to a set of fuzzy rules. Fuzzy logic is particularly advantageous in addressing intricate and uncertain situations, whereby conventional crisp logic may prove inadequate. Fuzzy logic is widely utilized in many domains such as control systems, artificial intelligence, decision-making, and expert systems due to its ability to offer a structured approach for representing uncertainty and conducting approximate reasoning.

Processing in fuzzy logic involves four steps. The first step is fuzzification where data input is converted into "fuzzy form". In this step, the inputs are mapped to determine their membership and each of them is given a membership degree. Next, the result of fuzzification enters the rule evaluation process to figure out which rule is suitable regarding their membership degrees using logical operators such as "AND" and "OR". Once the fuzzy rules have been evaluated, the consequence membership degrees which are derived from the evaluation process are aggregated by the system. In case of overlapping antecedents that result in multiple effect activation, the aggregation process takes into account combining their membership degrees to generate a single membership value in the output domain. Defuzzification is the final stage in the fuzzy inference procedure. Defuzzification is the process of transforming an aggregated fuzzy output into a precise (non-fuzzy) value. There are numerous defuzzification techniques available, including centroid, maximum, and weighted average. The method of defuzzification chosen is dependent on the application and system requirements. The fuzzy logic type that is used in this thesis is Takagi-Sugeno-Kang and it is explained in the later part.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a model that correlates input and output using biological neuron work principles (Krishnachandran, 2016). This model uses three-layer hierarchies namely input, hidden, and output layers. The input layer consists of neurons that accept data input while the hidden layers are located between the input and output layers. The hidden layers have the objective to assist the network to handle input complexities. Lastly, the results are produced by the output layer after the layer process the feed from hidden layers.

ANN uses a set of formulas in order to process incoming information and then generate output. The set is named an activation function that has several forms such as threshold, step, sigmoid, linear, and gaussian functions. The learning algorithm for ANN is divided into two steps with namely of forward phase and the backward phase. In the former phase, the neurons calculate the output by processing data input using the activation function in sequence while the later phase involves weights or parameters adjustment after comparing the actual and desired output. The learning method that is commonly used in the backward phase is Gradient Descent and it will be explained in the later part.

ANFIS Architecture and Operation

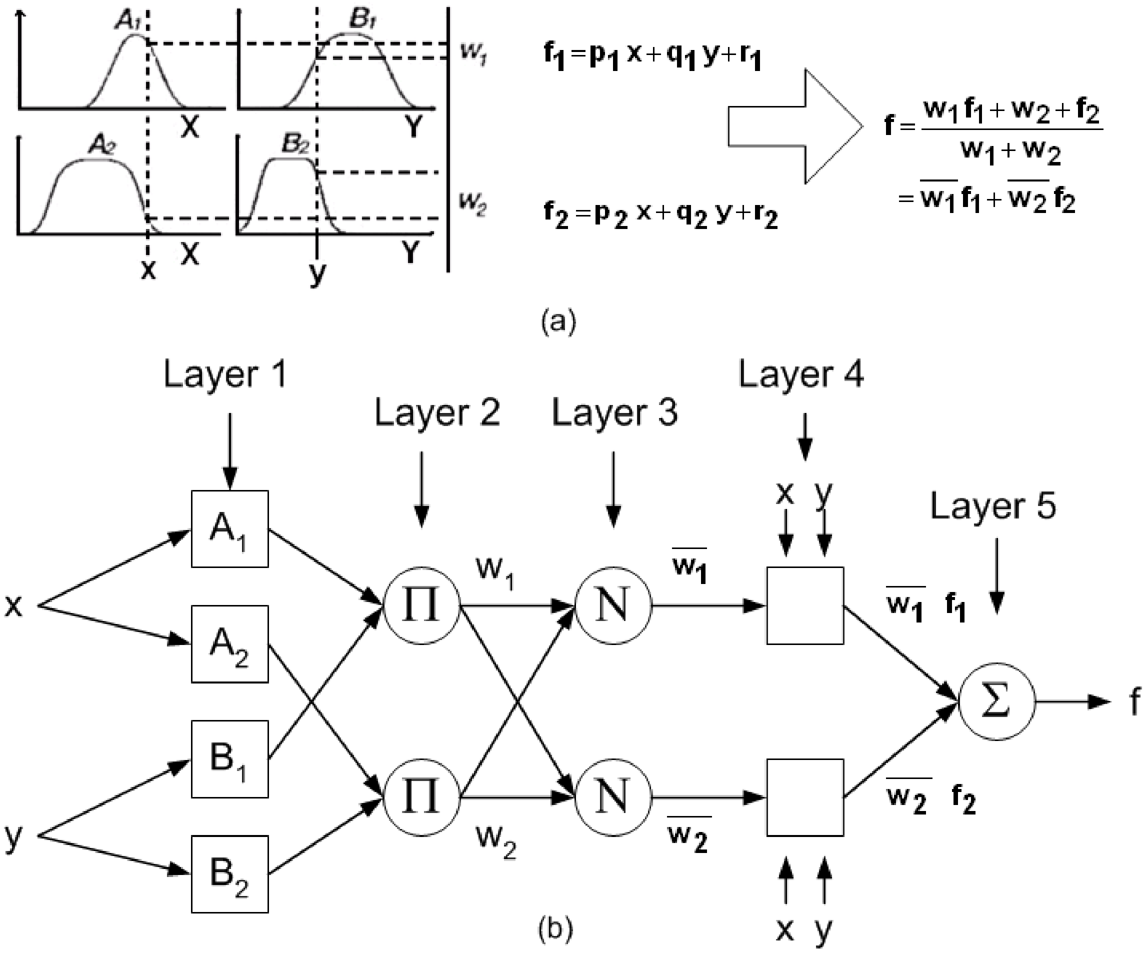

Figure 3-1 Fuzzy Inference System (a) and an example of ANFIS block diagram (b) (Joelianto et al., 2013)

The Adaptive Neuro-Fuzzy Inference System shown in **Figure 3-1**(b) generally consists of five layers in its architecture and it was initially developed by Jang et all (1997). As its name, some of the layers are adaptive or the parameters in those layers will be adjusted during the backward learning process. Two types of fuzzy logic systems are generally used in ANFIS for establishing the consequence part of the rules that are Tagaki-Sugeno-Kang (later called TSK or Sugeno) or Mamdani. This thesis uses Sugeno rules as it is more efficient in calculation, suitable in mathematical models, and flexible. The rule set commonly used for a first-order Sugeno fuzzy system, consisting of two fuzzy if-then rules, is provided by :

- If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
- If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

Each layer is explained in detail as follows based on **Figure 3-1.**

Layer 1

This layer is an initial step to define the membership grade of input x and y in correspondence to fuzzy sets A and B using **Equation 3.5**. The membership grade is calculated by **Equation 3.6 and 3.7**. The parameters of c and σ are determined during backward learning.

(3.5) $$A_i = \mu_{ai} \, ; \, B_i = \mu_b$$

(3.6) $$\mu_{ai}(x) = \exp(-0.5\,(\tfrac{x-c}{\sigma})^2)$$

(3.7) $$\mu_{bi}(y) = \exp(-0.5\,(\tfrac{y-c}{\sigma})^2)$$

i = 1,2

Layer 2

One of the non-adaptive layers in ANFIS is the second layer which has an objective to calculate the weight of each fuzzy rule using **Equation 3.8**. The other name of this layer is antecendent layer (indicated by Π).

(3.8) $$W_i = \mu_{ai}(x) \bullet \mu_{bi}(y)$$

i = 1,2

The operator that are used in equation is product t-norm fuzzy logic and the parameters of the equation are constant.

Layer 3

Another non-adaptive layer in ANFIS (indicated by N) is the third layer that normalize the output from the second layer using **Equation 3.9**.

(3.9) $$\overline{w} = \frac{w_i}{w_1 + w_2}\text{, i = 1,2}$$

Layer 4

This adaptive layer consists of consequence parts of Sugeno Fuzzy rule. This layer processes the previous layer output using **Equation 3.10** that have p,q and r as their constant. Later, the values of p,q, and r would be changed within the learning process.

(3.10) $$\overline{w_i}\, f_i = \overline{w_i}\,(p_i x + q_i y + r_i)\text{, i = 1,2}$$

Layer 5

The last layer of ANFIS aggregates all of the consequence output to generate one output using **Equation 3.11**. This layer is categorized as non-adaptive layer since the layer only process the input using certain formula without adjusting parameter during learning process.

(3.11) $$\sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \text{ i = 1,2}$$

Principally, the layers represent the process of Fuzzy system to generate outputs but if fuzzy stands alone, the parameters in the adaptive layers shall be adjusted by trial and error. Furthermore, the ANN learning methods are utilized to adjust adaptive parameters. ANFIS utilizes hybrid learning algorithms which are combination between Error Backpropagation (EBP) or Gradient Descent as well as Recursive Linear Square Error (RLSE) to optimize the result. The parameter of c and σ are set by gradient descent methods while the linear consequent parameters in the fourth layer are updated by RLSE.

Gradient Descent

This method utilizes gradient to determine the center and σ in the membership degree formula. The gradient is resulted from the output errors which is gotten from the actual and targeted output differentiation. Next, the gradient become the factor to calculate the new number of learnable parameters. The steps are repeated until the desired error is achieved. The illustration of this method is shown by **Figure 3-2**.

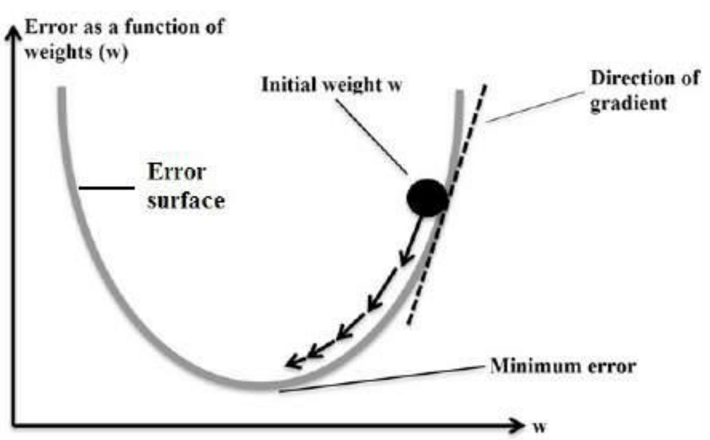

Figure 3-2 Gradient Descent Illustration (Krishnachandran, 2016)

Recursive Least Square Errors (RSLE)

RSLE is generally applicated in an linear equation to estimate its coefficient. This thesis uses the method to update the consequent parameters which are in linear equations. The main aim of RSLE is minimizing the cost function by changing the coefficients in the function when new data come. The working principle of RLSE is explained by **Figure 3-2**.

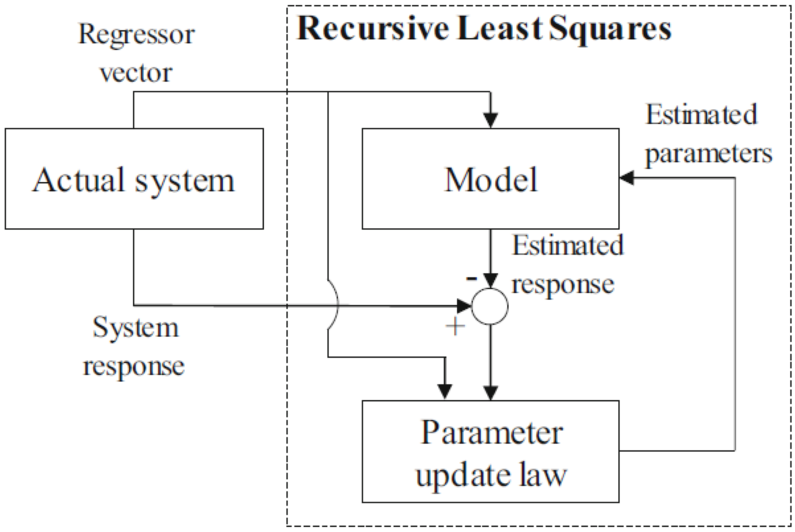

Figure 3-3 Recursive Least Square Diagram (Lee *et al.*, 2020)

3.3. Genetic Algorithms

Natural selection and genetics are the main principle in genetic algorithms which was pioneered by J.H. Holland in 1962. The main objective of genetic algorithms is finding the optimal global solution from a possible solution population. Genetic algorithms are widely used in solving optimization problems in many areas such as control systems and machine learning.

Key Components of Genetic Algorithms

Because of inspired by nature, there are equal parameters among genetic algorithms, natural selection, and genetics concepts in biology. Nevertheless, the meanings of parameters are adjusted in term of optimization problems. For solution representation, GA uses the term population and chromosome. The population consists of all of possible solutions while chromosomes is a certain solution for the given problems. Each individual is given a fitness value to represent its behavior in the given problems. An illustration of the parameters is described in **Figure 3-4**.

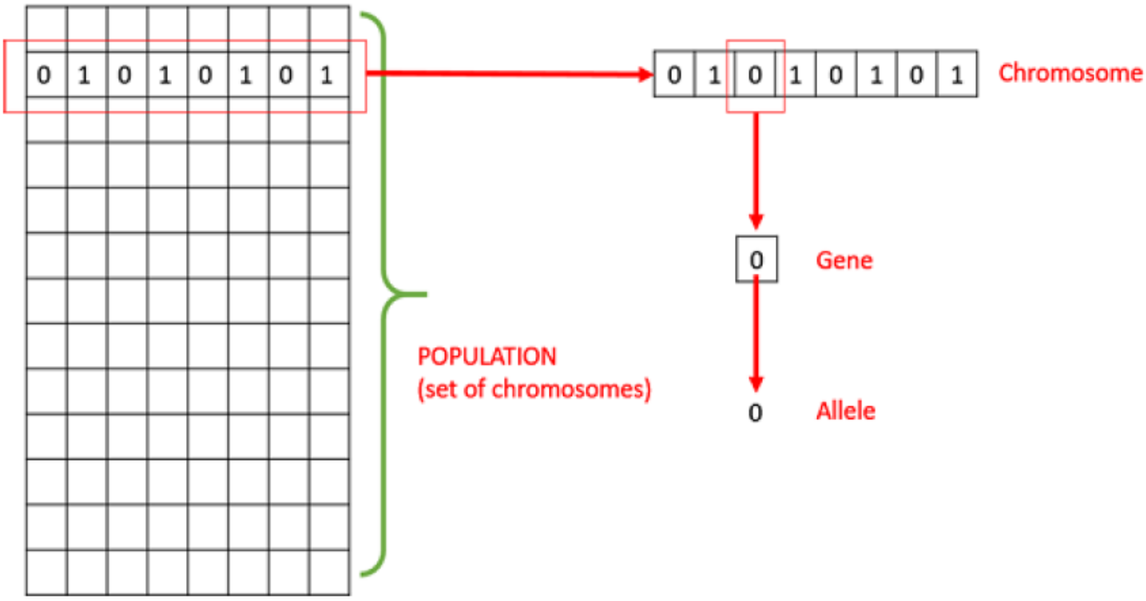

Figure 3-4 The parameters Illustration (J.C Bose University Lecture Team, 2021)

Random, tournament and roulette wheel are the selection method commonly applied in genetic algorithms. In Random selection, the parents are selected randomly without applying certain criteria. Despite the random selection is easier to be implemented, the selection is least favorable to use due to uncertainty in its results. The tournament selection (**Figure 3-5**) gives opportunities to choose individuals to become parents and the best one will be selected. Then, the process is repeated to find the next parent.

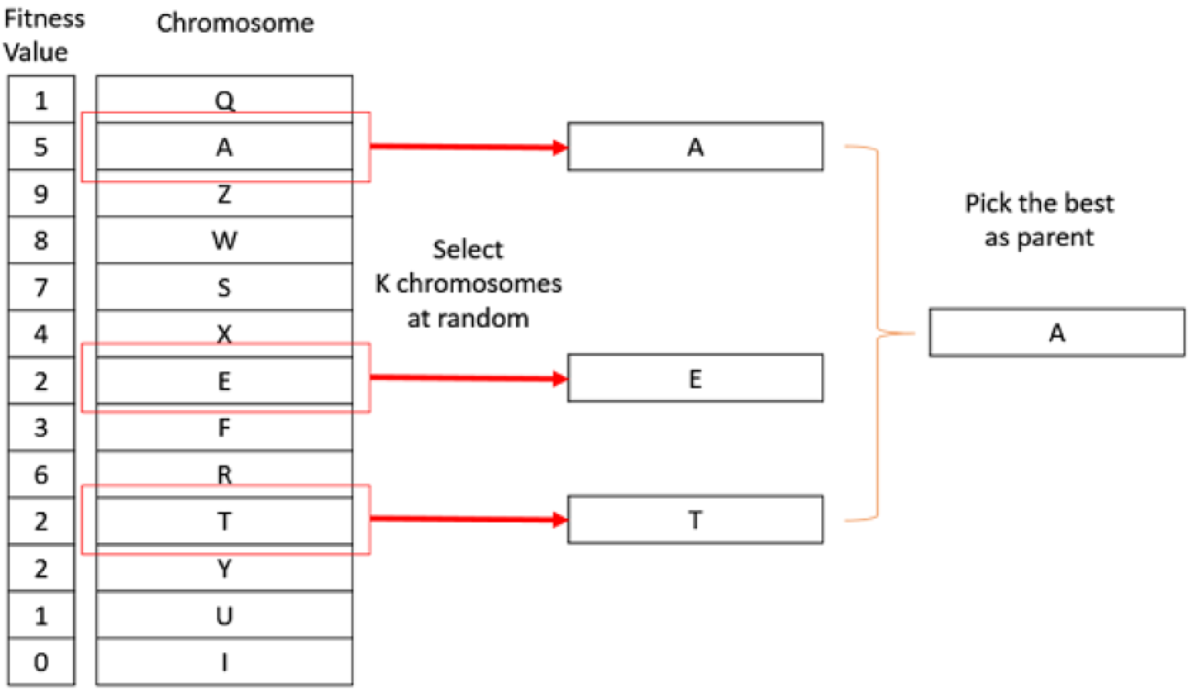

Figure 3-5 Tournament Selection (J.C Bose University Lecture Team, 2021)

The last common method is the roulette wheel which is illustrated in the **Figure 3-6**. In this method, a fixed point is placed on the wheel circumferences and then the wheel is rotated. The higher fitness value has a wider proportion in the wheel so the probability of the higher fitness chosen is bigger. Once the wheel rotation stop, a parent is selected by the fixed point. The next parent will be selected using equal steps.

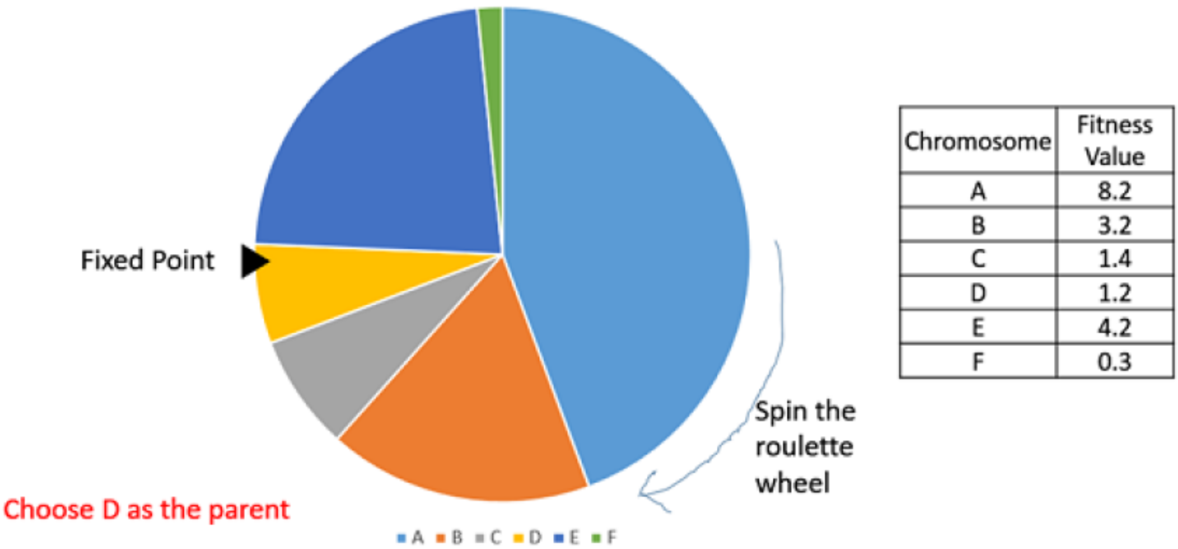

Figure 3-6 Roulette Wheel Selection (J.C Bose University Lecture Team, 2021)

In terms of genetic operators, the GAs follow crossover or recombination as well as mutation principles. The crossover is categorized into three common types, for instance single point (**Figure 3-7**), multi-point (**Figure 3-8**) and uniform crossover (**Figure 3-9**). To produce new offspring, a random crossover point is chosen, and the tails of the two parents are switched in one-point crossover whereas the multi-point uses equal stages with the one-point but the number of chosen points is more than one. Different from the two previous crossover types, the chromosome is not divided into parts, but rather each gene is treated singly in the uniform crossover. Uniform crossover occurs when the genetic material from the parents is randomly transferred, gene by gene, to produce a new child. A random binary mask is created for each gene location on the chromosome. The mask defines which parent's gene will be inherited in the offspring at that place.

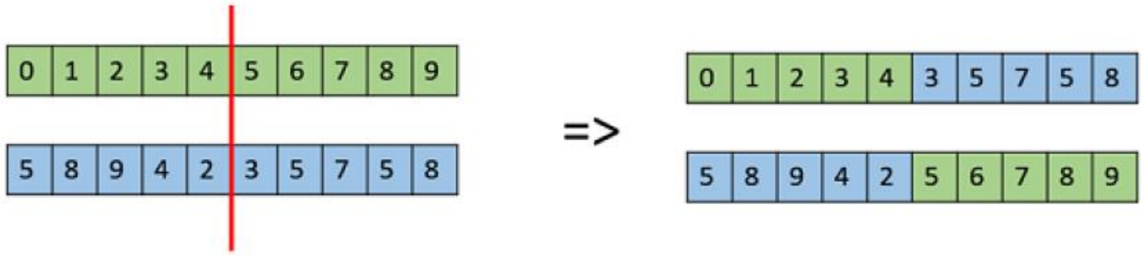

Figure 3-7 Single Point Crossover (J.C Bose University Lecture Team, 2021)

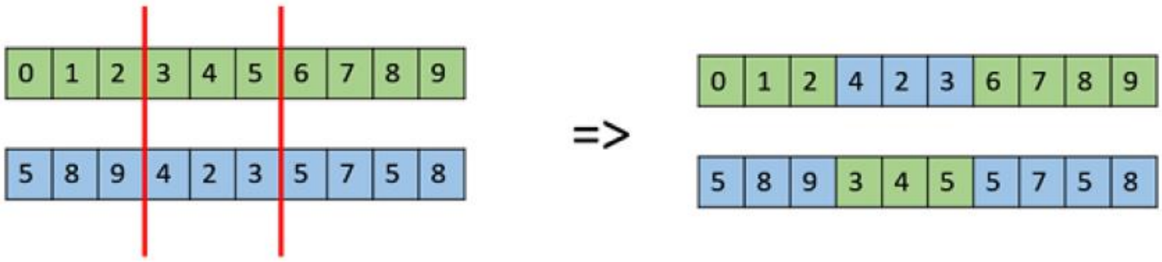

Figure 3-8 Multi-point Crossover (J.C Bose University Lecture Team, 2021)

Figure 3-9 Uniform Crossover (J.C Bose University Lecture Team, 2021)

The mutation is a genetic operator in Genetic Algorithms (GAs) that is used to create random changes in individual solutions within the population. The goal of mutation is to promote population variety and prevent early convergence to undesirable solutions. Mutation allows the GA to explore new parts of the solution space that may not be accessible through other genetic operators such as crossover by introducing randomness to individuals' genetic material.

Working Principle of Genetic Algorithms

Similar to other machine learning methods, GA is started by initialization to create a population that is filled with random or heuristic solutions. Each solution is represented in the population as an individual, generally in the form of a chromosome or genome. The parameters or variables that determine the solution space are encoded by the chromosomes.

Following the initialization of the population, each individual's fitness is assessed using a fitness function. The fitness function measures how well an individual performs in the problem area. In optimization issues, the fitness function may be the objective function that the GA is attempting to maximize or decrease. The greater the fitness value, the better the individual's performance.

After determining the fitness values, the GA picks solutions or parents from the population to form the foundation of the next generation. Individuals with greater fitness values are preferred in the selection process because they are more likely to pass on beneficial features to the following generation. There are several techniques of selection, including roulette wheel selection, tournament selection, and random selection.

The crossover stage combines selected people (parents) to produce new offspring (children). In biology, genetic recombination inspires crossover. It entails parents swapping genetic material at random locations along their chromosomes. Crossover encourages solution space exploration and allows the GA to produce alternative solutions that mix advantageous features from multiple parents.

Mutation is the process by which minor random changes are introduced into the genetic material of individual chromosomes. It contributes to population variety and keeps the GA from being locked in local optima. During mutation, certain genes on a person's genome are randomly changed. To retain information from the parents, the mutation rate is normally maintained low.

The following generation is made up of freshly generated children as well as a component of the original population. This stage follows the theory of "survival of the fittest," which states that people with higher fitness levels have a better chance of being chosen for the following generation. This method guarantees that promising solutions are more likely to be retained and built upon in future generations.

The GA progresses across generations, with the processes of selection, crossover, mutation, and replacement repeated repeatedly. The GA will continue until a termination condition is satisfied. Termination requirements might include attaining a certain number of generations, achieving a certain level of fitness, or crossing a preset convergence threshold. The working principle of GA is described by **Figure 3-10**.

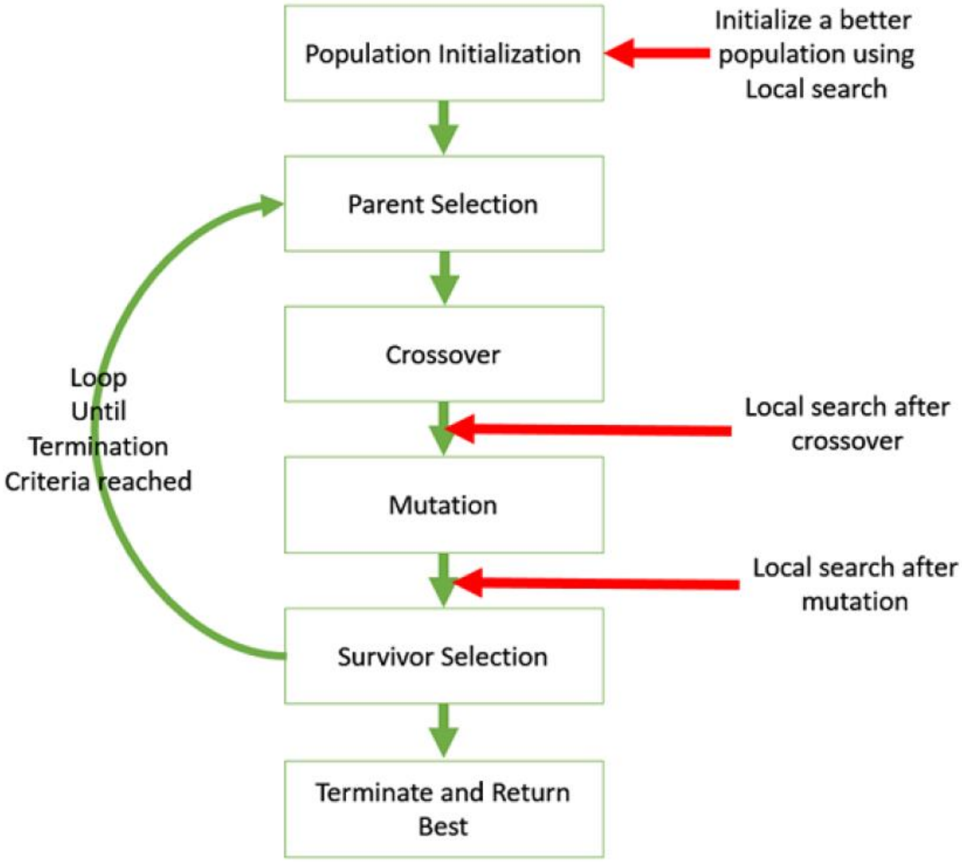

Figure 3-10 Genetic Algorithms Working Principles (J.C Bose University Lecture Team, 2021)

Advantages and Limitations of Genetic Algorithms

in terms of GA applications, the users should give concerns with GA's advantages and limitations. The upper hand of GA is mainly in resolving complex problems which have a huge number of parameters. Other benefits of the algorithms are providing not only one solution but also some solutions so the users could choose their desired optimization level. The ability of GA to work in models with limited data availability could be considered as one of its advantages. Also, GA could be suitable to work in discrete, continuous, and multi-objective models.

On the other hand, it would not be recommended to use GA in simple problems with much derivative information. In addition, GA could involve time-consuming calculations for iterating fitness values in certain problems. Furthermore, the solutions that are generated by GA depend on the initial parameter provided by the users.

GA takes a role to tune classical ANFIS parameters in this thesis. The rules, membership functions and consequent parameters of ANFIS are optimized by this metaheuristics algorithms to minimize the model error. Parameter selection basis for the Genetic Algorithms is detail explained in chapter 4.

3.4. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is another algorithm that is inspired by nature and it was introduced by James Kennedy and Russell Eberhart. More specifically, PSO is inspired by animal social behaviors such as bird flocking, swarming, and fish schooling. PSO could be used by simple mathematics notations and it is not a gradient-based method which is different from gradient descent. Typical with genetic algorithms, PSO is started by initiating a population and finding the best solution within the population. Another similarity between them is their application fields including parameter optimization in machine learning.

Key Concepts of Particle Swarm Optimization

Particle Swarm Optimization as its name uses the term particle to denote a solution for given problems. The position of each particle in a search space reflects a potential solution. To find the best solution, the particles travel to different regions in the solution space. Each particle’s location is generally represented as a vector in a multidimensional space.

The swarm is formed of several particles that work together to find the optimum solution. There are communications among particles by exchanging information about their best-found location. This collaboration aims to direct the swarm to promising areas of the solution space. The flocking birds' or schooling fish's social behavior is the main inspiration for the swarm dynamics and interactions.

Assessment of the swarm particle performance could be done by the fitness function which measures the relativity of the particle’s location corresponding to the optimization problem’s objective. The quality of the particle’s position in the optimization space could be indicated by the particle’s fitness function. The form of the fitness function is usually the objective function in either minimization or maximization problems.

The velocity of each particle determines its movement in the search space. A vector represents the velocity and it contains information about the direction and speed of the particle. The velocity, including its component (the direction and speed), uses three components as the basis for updating, namely pbest, lbest and gbest. The first term refers to the best position that could be achieved individually by a particle while lbest has equal meaning with pbest but it is performed by the teammates. gbest is the best solution discovered by any particle in the whole swarm. It directs all of the particles to a promising location in the solution space. The vectors combination is depicted by **Figure 3.11**.

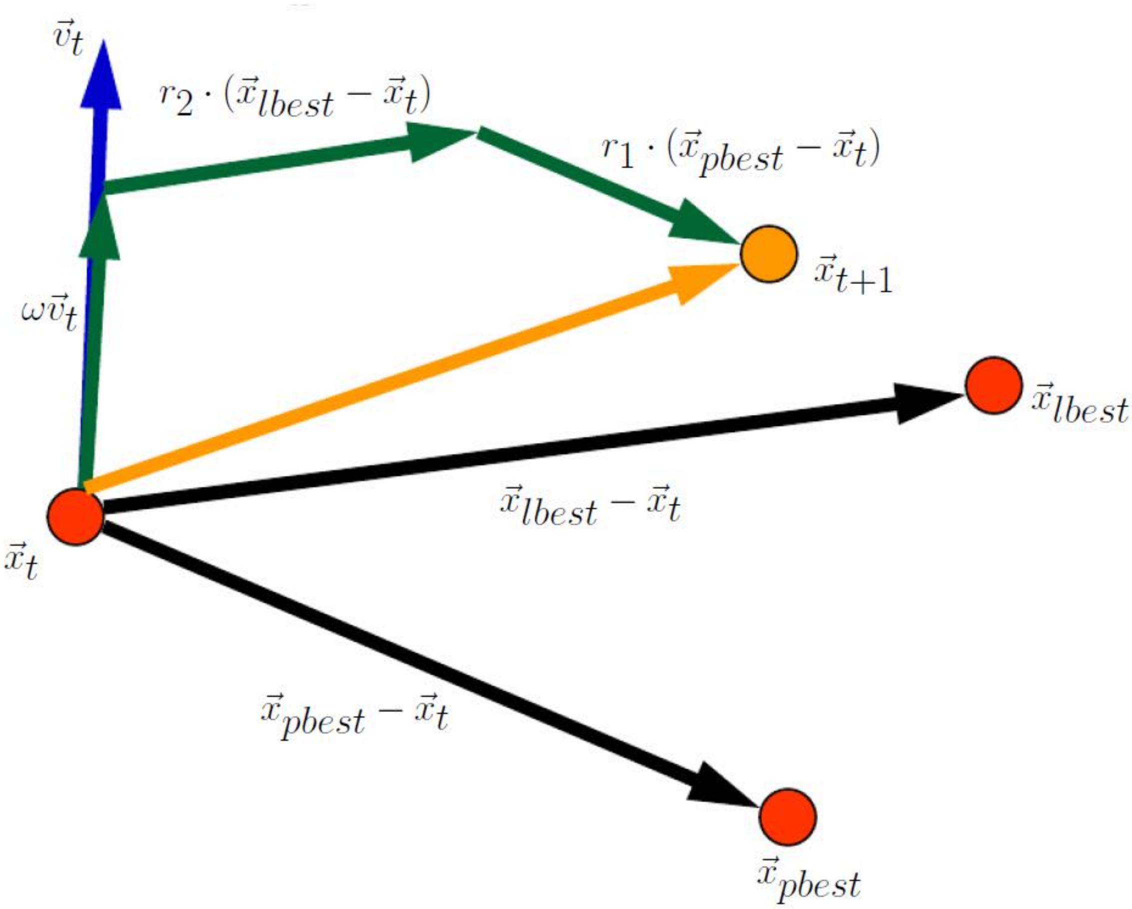

Figure 3-11 Particle Vectors Combination (Di Caro, 2018)

Steps of PSO Implementation

Step 1: Initialization of the Swarm with Random Particle Positions and Velocities

The PSO mechanism starts from the formation of a swarm of particles, each representing a possible answer to the optimization issue. The swarm is started with a certain number of particles that are randomly dispersed over the solution space. Each particle is given a random location and velocity vector. The position vector represents a potential solution by defining the particle's current location in the solution space. The velocity vector specifies the direction and speed of the particle's travel.

Step 2: Evaluation of Fitness for Each Particle in the Swarm:

Following the initialization of the swarm, the fitness of each particle is evaluated using the fitness function. The fitness function assesses how well each particle's location performs in relation to the goal of the challenge. The particle's performance in the issue domain improves as the fitness value increases. The fitness value is computed based on the particle's present location during the fitness evaluation. During the optimization process, the fitness function acts as the aim to be maximized or decreased.

Step 3: Updating the Personal Best and Global Best Positions for Each Particle

After evaluating the fitness of each particle, personal best position (pbest) and global best position (gbest) are updated. The particle's movement is guided toward promising regions of the solution space by its personal best and global best locations. Particles communicate with the whole swarm about their own best positions and the global best positions.

Step 4: Particle Movement Based on Velocity and Position Update Rules

With their personal best and global best positions updated, the particles change their velocities and locations using a following three-component velocity update algorithm. **Equation 3.12** outlines the correlation between the velocity of a particle and the entities involved.

- Inertia Component: The component of inertia permits particles to retain some of their former velocity, assisting them in maintaining orientation and avoiding premature convergence. It is governed by a quantity known as the inertia weight (w).
- Cognitive Component (Personal Attraction): The cognitive component draws a particle to its optimal place. It is regulated by a variable known as the cognitive parameter (c1).
- Social Component (Global Attraction): The social component draws a particle to the swarm's global optimal position. It is regulated by a variable known as the social parameter (c2).

(3.12) $$V_i^{t+1} = wV_i^t + C_i\,U_i^t(pb_i^t - p_i^t) + C_2\,U_2^t\,(gb^t - p_i^t)$$

where:

V_i^t = the velocity of particle i at time step t.

p_i^t = the position of particle i at time step t.

pb_i^t = the personal best position of particle i at time step t.

gb^t = the global best position found by the swarm at time step t.

w, C_i , and C_2 are the inertia weight, cognitive parameter, and social parameter, respectively.

Step 5: Termination

For a defined number of iterations or generations, PSO continues to update the velocities and locations of particles depending on the velocity update rule. The termination criteria specify when the PSO procedure should be terminated. Reaching the maximum number of iterations, getting the desired fitness value, and reaching the preset convergence threshold are all common termination circumstances. The PSO process finishes when the termination condition is fulfilled, and the best solution identified (the global best position) indicates the optimum or near-optimal solution to the optimization problem.

The present thesis incorporates the use of a Particle Swarm Optimizations (PSO) to optimize the parameters of a traditional Adaptive Neuro-Fuzzy Inference System (ANFIS). The metaheuristic algorithms are employed to optimize the rules, membership function, and consequent parameters of ANFIS in order to reduce the model error. The selection criteria for parameter selection in Particle Swarm Optimization are thoroughly elucidated in Chapter 4.

Chapter 4. **Methodology**

Regarding the research questions, some steps have to be implemented to get the optimal BDTI predictors and compare their performances. This chapter explains each stage from data collection to the models' performance evaluation. The related parameters which need to be adjusted are also informed in this chapter including the basis for determining them. Chapter 4.1 describes data collection, statistical analysis, and data clustering, Chapter 4.2 discusses the modeling phase, and Chapter 4.3 explains how to examine the models' accuracy based on some statistical parameters. Microsoft Excel is utilized to conduct data analysis and MATLAB 2020a has a significant role in forming the models.

4.1. Data Analysis

Data Preparation and Selection

This thesis considers Brent Oil price, ARCA Oil, S&P 500 Volatile Index, Dow Jones Marine Transportation Index, MSCI World Marine Index, Shanghai Stock Exchange Composite Index (SSECI), Gold Price, and CRB index as the candidate inputs while the output is only BDTI. the data are captured from some internet resources such as Clarkson (BDTI and Brent Oil Price), Investing.com (CRB, ARCA Oil, S&P 500 Volatility Index, and gold future price), Yahoo Finance (SSECI) and Onvista (Dow Jones Marine Transportation Index and MSCI World Marine Index) which come from January 2008 to December 2019.

The sampling time for every indicator is monthly basis but some of the raw data are on a daily basis. Consequently, they need to be converted on a monthly basis by averaging the data. After the adjustment has been done, the data statistics indicators are examined to decide inputs and data portions for training and validation purposes. Statistics analysis is conducted by Microsoft Excel. The coefficient of correlation which represents the relationship between two data from different categories is the first key statistic parameter to be checked. The parameter has three main values which are -1, 0, and 1. The zero value means that the data do not have a relationship while -1 and 1 could be interpreted as the inverse and noncontradictory relationship in turn. In this thesis, the input variables with the three highest values of coefficient of correlation with avoiding the sign are chosen as the model inputs.

On the other hand, as the coefficient has a downside in describing the relationship, this thesis utilizes another statistic coefficient which is the coefficient of determination. This coefficient which is the square of the coefficient of correlation could elaborate the relationship specifically. The coefficient tells us that how much percentage of data could be explained by their counterpart data. Nevertheless, we should remember that all of the coefficients only represent relationships but not causality (Keller, 2014). In order to make sure all of the input candidates not only show the relationship but also the causality to BDTI, study literature should be conducted as figured in **Table 2-2**.

The other statistics parameters that have an important role in this thesis are data range, maximum, and minimum data value. The data range that is the differential between maximum and minimum data shall be most considered to determine which part of data to become training and validation data along with the maximum and minimum data themselves. The validation data should have equal or lower maximum values as well as equal or higher minimum values than the training dataset which has a ratio of 80:20 with the validation dataset. Furthermore, it is important to ensure that the range of data in the training dataset is either equal to or greater than the range of data in the validation dataset. Additionally, the calculation of data averages or means plays a crucial part in evaluating the performance of models, as it is used for comparison with the root mean square error (RMSE) to assess model performance. This phase will be elaborated upon in subsequent sections.

Data Clustering

The clustering process in the data, as mentioned before, is the one of methods to generate initial FIS in the ANFIS system. This thesis uses subtractive clustering since it is an established method to initiate FIS before it undergoes the learning process. Some parameters which are ra, squash factors, accept ratio, and reject ratio need to be adjusted to optimize the clustering process. As the best combination is determined by a trial and error process, This thesis refers to several papers to determine the parameters and then combine them. **Table 4-1** shows the parameters that are used in this thesis. All of the parameter combinations in this process are combined with ANFIS learning parameters in the next step and then a performance examination is conducted.

Table 4-1 Subtractive Clustering Parameters

Parameters	Number	Reference(s)
Radius	0.2 - 0.7	(Chiu, 1997 & Hammouda and Karray, 2000)
Squash Factor	1.25	(Chiu, 1997)
	1.5	(Chiu, 1994)
Accept ratio	0.5	(Chiu, 1994)
Reject Ratio	0.15	(Chiu, 1994)

4.2. Modeling

Classical ANFIS (Model 1)

The first model employed in this thesis adheres to the conventional ANFIS model as defined in Chapter 3.2. The learning algorithm of the model incorporates the use of gradient descent and recursive least squares estimation (RLSE). In order to enhance the efficiency of the learning process, the determination of the step size is of utmost importance. In the process of learning, the adaptive step size values are decided by the initial step size, the rate at which the step size increases, and the number of times the step size decreases. The alteration of step size values corresponds to two primary principles, as outlined in **Figure 4.1**. It was suggested that the rate at which the step size increases and decreases should be 1.1 and 0.9 times the present values of the step size, respectively (Jang, 1993). In the present thesis, the parameters are initially assigned identical values, with an initial step size of 0.1. The default value for the iteration number is set to 5000 in order to allow a small initial step size. In several cases, the process of iteration should be terminated prematurely in order to mitigate the issue of overfitting. The parameters are fine-tuned to maximize the model following the amalgamation of the original values. This study suggests employing a ratio between the root mean square error (RMSE) and the average of the data as a means of first evaluating the correctness of the model. The desired accuracy range for both training and validation, with respect to the ratio, is set below 0.15 (15%) for training and below 0.25 (25%) for validation. The model that exhibits the highest level of optimization is chosen to undergo tuning through the utilization of Genetic Algorithms and Particle Swarm Optimizations.

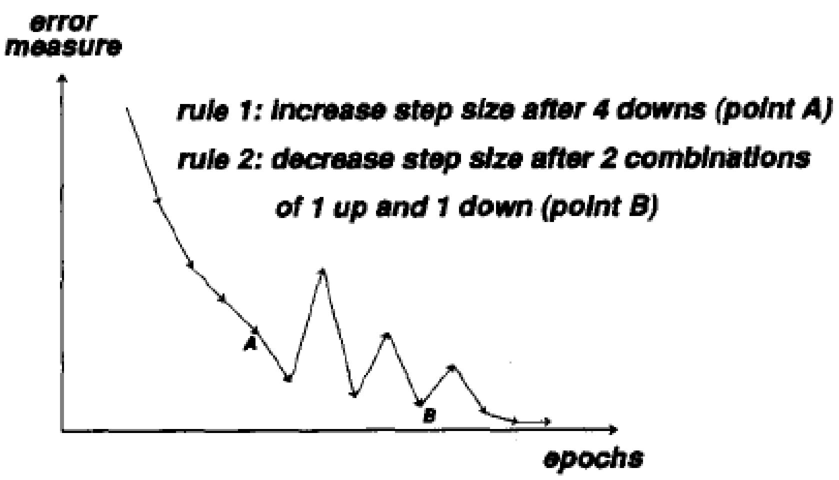

Figure 4-1 Updating step size values (Jang, 1993)

ANFIS – GA (Model 2)

In this model, the most optimal parameter combination that is extracted from the first model is improved by the genetic algorithms. To prevent many trials to find the most optimal condition, this thesis uses some references to initiate the variables and also limits to several parameters, namely population size, maximum stall generations, selection function, elite count, crossover fraction, mutation, and crossover function. Other parameters follow the default number and variable in Matlab R2020a. The population size is set to 150 to reduce calculation time and make sure that the solution choices are sufficient. The number comes from the middle number of moderate population size (Hassanat *et al.*, 2019). This thesis suggests the maximum stall generations equal to the maximum generation which are 1500 generations to prevent early stop in the learning process. This thesis employs tournament and roulette wheel selection methods, which are widely employed in the field of genetic algorithms (Azizpor *et al.*, 2021), for the purpose of selecting individuals. Numbers 0, 3, and 7 are considered to become the number of elite count in this thesis because the smaller number of elite count leads the solution to the global minima (Mishra and Shukla, 2017) and the default number of elite count in Matlab is 5 % of total population or approximately 7.

In terms of Crossover fraction, Alarifi in 2019 used 0.7 in his optimal model while Mishra and Shukla in 2017, Ravi et al. in 2011, and Ayad et al. in 2012 set 0.8 in their model. A bigger number (0.9) of the parameter was tested by Lavinas et al. in 2018 to examine the effect of population size. To accommodate all of the numbers, this research uses a range between 0.7 and 0.9 to generate the second model initially. The Crossover intermediate is utilized as the crossover function due to its ability to handle linear constraint (Matlab, 2023) and the ratio for this function is 0.5 as it was successfully applied in many fields (Mühlenbein and Schlierkamp-Voosen, 1993). The last function, the mutation adaptive feasible function, is selected in this research because of its adaptive skill regarding the last failed or successful generations (Matlab, 2023). Similar to the previous model, all of the parameters are combined and then the most optimal one becomes the basis for further trials to find the final model form.

ANFIS – PSO (Model 3)

The last model is a hybrid model between ANN and Fuzzy System which is tuned by Particle Swarm Optimization. Before designing the model, A literature review is undertaken to ascertain the parameters utilized and the corresponding quantity of input for each parameter. Maximum iterations, maximum stall iterations, self-adjustment weight, social adjustment weight, inertia weight, and swarm size are the variables that need to be adjusted in order to produce the optimum model. Oliveira and Schirru in 2009 recommended that the inertia weight should be

0.729 and the self and social adjustment weight should be 1.49. In addition, they used a different inertia weight when his model was learning. Initially, they set 0.9 and then decreased it linearly to 0.4 at the end of the learning phase. On the other hand, Rini et al. in 2013 proposed the value of self-adjustment weight was 0.5 and social adjustment weight was 1 with 50 for the number of swarm sizes. Alarifi et al. in 2019 found that the values of self and social value were 1 and 2 respectively in his final model with only 20 swarms. DiRiK and Gül in 2021 set 1200 for maximum iterations, 1 for the self-adjustment weight and inertia weight, 2 for the social adjustment weight, and started from 20 to 40 for the particle number. Pedersen and Chipperfield in 2010 experimented PSO model with the following parameter range: Swarm size {1,200}, inertia weight {-2, 2}, self-adjustment weight {-4, 4}, and social adjustment weight {-4,4}.
Based on the study literature, Some numbers are chosen to be combined and the most optimum combination is considered to compare with the other two models. The third model limits the iteration to 1500 and the same number is also applied for the maximum number of stall iterations to produce a more optimal model. This research set the inertia weight to be adaptive with the range of 0.4 and 1 (Shi and Eberhart, 1998 & Alarifi *et al.*, 2019). Swarm size, self-adjustment weight, and social adjustment weight values are set to be variable. The size begins from 50 to 100 while self-adjustment weight and social adjustment weight have [0.5, 1, 1.49] and [1, 1.49, 2] respectively in initial trials. Then, the characteristics and number of the most optimal model from the initial model become a basis for further trials to generate the final model.

4.3. Models Evaluation

Several metrics are used to measure the performance of each model which are RMSE, CVRMSE, MAE, and MAPE. Walker et al. in 2019 set the limit of CVRMSE and MAPE at the level of 30 % and 20% respectively in order to compare machine learning algorithms to predict energy in commercial buildings. Esfahanipour and Mardani in 2011 proposed an ANFIS model to predict stock prices in the Tehran Stock Exchange with MAPE values of about 40%. Also, Boyacioglu and Avci in 2010 used CVRMSE as the one of parameters to measure ANFIS performance to forecast stock market return in the Istanbul Stock Exchange with the range of 45.81 – 89.46 % in the final result. This thesis uses the proposed limit by Walker et al. in 2019 since this research uses several machine-learning algorithms and the limits are acceptable in terms of accuracy. An exception of the rule occurs in the first model of this research and it is explained in the next chapter in detail. CVRMSE is the first parameter to be examined to decide the final form from each model and then MAPE number of the final model is checked. If the

MAPE values are above the limit, the trial process would be continued. Meanwhile, the remaining performance metrics (RMSE and MAE) outlined above will contribute to a more comprehensive understanding of the forecasted outcomes. The examinations are applied to each model using both training and validation data. The explanation of the validation metrics is as follows.

RMSE

The acronym RMSE denotes Root Mean Squared Error, a commonly employed metric across diverse disciplines such as machine learning, statistics, and engineering. Root Mean Square Error (RMSE) is a statistical metric that quantifies the average magnitude of discrepancies between projected values and observed values. The process allows for the quantification of the precision of a predictive model by an evaluation of the degree to which its predictions align with the actual data. The mathematical computation of the Root Mean Square Error (RMSE) involves the extraction of the square root of the mean of the squared errors between the predicted values and the matching actual values within a given dataset. A lower value of RMSE means that the model is better. The formula of RMSE is shown by **Formula 4.1.**

(4.1) $$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{n}\left(y_j - \overline{y_j}\right)^2}{N}}$$

Where:

y_j= actual value at period j

$\overline{y_j}$ = predicted value at period j

N = number of data

CVRMSE

The coefficient of variation of the root mean squared error (CVRMSE) which could be calculated by **Formula 4.2** offers a standardized evaluation of the RMSE by comparing it to the average value of the target variable. This can be advantageous in scenarios when there is a significant disparity in the range of values exhibited by the target variable. A relative measure can be obtained by dividing the root mean square error (RMSE) by the mean. This allows for comparisons across different datasets or models while minimizing the impact of the target variable's size.

(4.2) $$\text{CVRMSE} = \frac{RMSE}{Average}$$

A smaller coefficient of variation of root mean square error (CVRMSE) implies that the model's root mean square error is relatively diminutive in relation to the mean, so indicating that the model's errors are relatively minor compared to the average values of the target. This can be particularly advantageous when one desires to assess the comparative prediction precision of various models on datasets characterized by dissimilar scales or units.

MAE

The Mean Absolute Error (MAE) is a metric used to assess the accuracy of a predictive model by calculating the average magnitude of the absolute differences between the projected values and the actual (observed) values. The Mean Absolute Error provides a straightforward approach to evaluating the overall error of a model's predictions, with less emphasis on the magnitude of the mistakes compared to the Root Mean Square Error (RMSE). The measure exhibits robustness in that it demonstrates less sensitivity to outliers compared to RMSE, as it does not incorporate the squaring of errors. This approach can offer benefits in situations involving datasets that include outliers or when there is a need for a measurement that does not disproportionately penalize significant deviations. Mathematically, MAE is determined by **Formula 4.3**.

(4.3) $$\text{MAE} = \frac{1}{N} \sum_{j=1}^{n} \left| y_j - \bar{y}_j \right|$$

Where:

y_j= actual value at period j

$\bar{y}_j$ = predicted value at period j

N = number of data

MAPE

The Mean Absolute Percentage Error (MAPE) is a metric that quantifies the average percentage deviation between projected values and actual (observed) values. It serves as a valuable indicator of the relative precision of a predictive model's projections. The Mean Absolute Percentage Error (MAPE) is a quantitative measure used to assess the accuracy of predictive models by calculating the average absolute percentage discrepancies between anticipated and actual values. It provides valuable insights into the extent to which a predictive model's forecasts align with genuine values. The utilization of this method is advantageous in comprehending the comparative precision of forecasts; however, it is imperative to exercise prudence when evaluating outcomes that involve limited or nonexistent actual data. This parameter follows **Formula 4.4** for calculation.

(4.4) $$\text{MAPE} = \frac{100\%}{N} \sum_{j=1}^{n} \left| \frac{y_j - \bar{y}_j}{y_j} \right|$$

Chapter 5. **Results and Analysis**

This chapter presents the findings derived from the research conducted, along with an analysis of these data. The fifth chapter of the study is structured into three primary sections, namely statistical analysis, model analysis, and performance analysis. The selection of inputs, training dataset, and validation partition in statistical analysis is explained by employing pertinent statistical factors. The subsequent section, known as model analysis, presents the outcomes of multiple trials conducted with each model, utilizing the initial parameters. This section also provides an examination of the optimization of the initial model and the rationale behind selecting a model as the final choice for comparison with models generated by different methods. The concluding section of Chapter 5 entails a comprehensive evaluation of model performance. The error metrics of each model are evaluated in order to discover the most effective algorithms for predicting BDTI.

5.1. Statistics Analysis

Correlation Analysis

The coefficient of Correlation is the first parameter to be examined since this parameter is essential to determine which chosen variables are for this research. **Table 5-1** shows the relationship between Brent Oil price, ARCA Oil, S&P 500 Volatile Index, Dow Jones Marine Transportation Index, MSCI World Marine Index, Shanghai Stock Exchange Composite Index (SSECI), Gold Price, and CRB index with BDTI in eleven years from 2008 to 2019 through two parameters, Coefficient of Correlation and Coefficient of Determination. The second parameter is utilized to give a comprehensive understanding of the model's input-output correlation.

Table 5-1 Input Candidates Correlation with BDTI

Variables	R	R^2
Brent Oil	0.21	0.04
ARCA Oil	0.23	0.05
S&P 500 Vol index	0.10	0.10
Dow Jones Marine US Transport Index	0.71	0.51
MSCI World Marine Index	0.60	0.36
SSECI	0.24	0.06
Gold	-0.34	0.12
CRB	0.42	0.17

According to the data presented in **Table 5-1**, it can be observed that the Dow Jones Marine US Transport Index, MSCI World Marine Index, and CRB Index have the highest R values. In relation to the R^2 values, it can be observed that more than 50% of the variability in BDTI value can be accounted for by the US Transport index. Conversely, the MSCI World Marine Index and CRB index are able to forecast just 36% and 17% of the variation in BDTI, respectively. In this thesis, the ANFIS models are constructed using three selected variables: the Dow Jones Marine US Transport Index, the MSCI World Marine Index, and the CRB Index. These variables are chosen as input parameters for the correlation analysis and the proposed model is shown in **Figure 5-1** The Proposed General Model Diagram

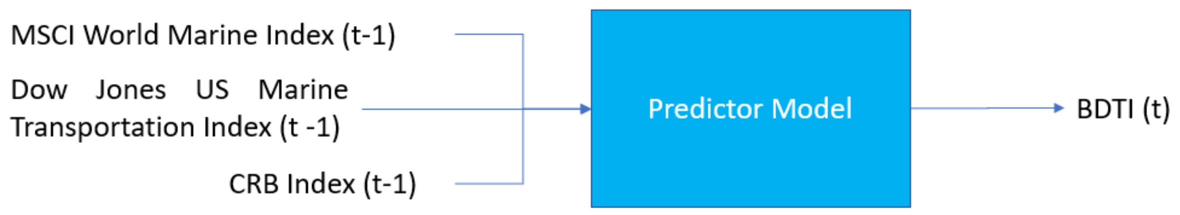

Figure 5-1 The Proposed General Model Diagram

Descriptive Statistics Analysis

The main objective of descriptive analysis in this thesis is to determine the part of data that would be assigned as training and validation data. As mentioned in the previous chapter, the maximum and minimum data of the validation dataset could not exceed the training dataset. A higher maximum data and/or lower minimum data than in the training dataset would lead to bigger values of the error system and could not to process the input properly.

In several cases in machine learning algorithms, the dataset is divided into training, validation, and testing data. This thesis employs hideout validation as opposed to cross-validation. Specifically, the dataset is partitioned into training and validation data sets with a ratio of 80:20. The Validation process is equal to the testing process in this type of validation since there is a separation between training and validation data. The Data coming from July 2017 to December 2019 are assigned as validation data while the remaining data are utilized to train the system.

Table 5-2 shows that the data separation fulfills the statistics requirement for not only the input but also the output of the models. For instance, the range of BDTI for validation data is 628.64 – 1421.76 which is within the training data range (477.84 – 2071.83). Another example is the MSCI World Marine Index from the input side. The variable's range in the training dataset (154.50 – 418.70) covers its range in the validation dataset (210.66 – 302.42).

Table 5-2 Statistics Parameters of Training and Validation Data

	Parameters	BDTI	MSCI World Marine Index	Dow Jones Marine US Transportation Index	CRB
Training data	Minimum Data	477.84	154.50	974.73	161.40
	Maximum data	2071.83	418.70	3553.02	441.16
	Range	1593.98	264.20	2578.29	279.76
	Mean	829.01	243.51	1689.09	271.90
Validation data	Parameters	BDTI	MSCI World Marine Index	Dow Jones Marine US Transportation Index	CRB
	Minimum Data	628.64	210.66	1340.59	178.56
	Maximum data	1421.76	302.42	1828.03	208.14
	Range	793.13	91.76	487.44	29.58
	Mean	815.61	246.46	1600.81	191.70

The mean or average is a statistical parameter commonly used to assess the central tendency of a dataset (Keller, 2014). The utilization of data averages can provide a suitable data context for placing the root mean square error (RMSE), which is one of the performance indicators. The interpretability of RMSE is challenging in the absence of contextual information about the data. To address this concern, the use of CVRMSE, a ratio between RMSE and the mean, might be employed. The essential function of this thesis is attributed to the average BDTI values in both the training data (829.01) and the validation data (815.61).

5.2. Models Analysis

Classical ANFIS Model (Model I)

As mentioned in the methodology section, the subtractive clustering parameters which are radius and squash factor are treated as variables while the remaining clustering (accept and reject ratio) as well as ANFIS learning parameters are constant to design this model in the first step. The initial step size, step size increase rate, step size decrease rate, accept ratio, and reject ratio are set to 0.1, 1.1, 0.9, 0.5, and 0.15 in turn during this step. The epoch numbers are also variable as the iterations are stopped once the difference between RMSE Training and Validation is minimal or the epoch number reaches 5000 to reduce calculation time.

This particular model incorporates distinct constraints compared to the other two models, as it will undergo tuning through the utilization of either Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO). In this model, it is imperative that the CVRMSE Training and Validation do not beyond 15% and 25% respectively as the upper limits. This phenomenon occurs when the model is optimized using either Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO), resulting in a decrease in the Training Coefficient of Variation of Root Mean Squared Error (CVRMSE), while the Validation CVRMSE tends to increase. The implementation of stricter limitations on the coefficient of variation of root mean square error (CVRMSE) in this model is expected to provide an opportunity for enhancement and mitigate the likelihood of ANFIS - GA and ANFIS - PSO CVRMSE validation beyond the original limit of 30%.

The numbers for parameters in trials number 1 to 12 in are **Table 5-3** conducted under the first step condition. Based on the trial list in **Table 5-3**, only trial no 9 aligned with the limitation because the percentage of CVRMSE training is below 15% and the CVRMSE validation is below 25% for validation. There are 11 trials that do not fulfill the criteria and four of them (Trial no. 5, 6, 11, and 12) do not have sufficient rule or only 1 rule is generated. As a consequence, they could not undergo ANFIS learning.

The main cause of that condition is their high radius value. Regarding the concept of subtractive clustering, a higher radius value results a wider influence of the cluster center and the number of cluster center reduction. Then, the cluster center will become the center of membership function and its influence the forms of membership function in the antecedent part during the initial FIS generation of ANFIS learning. In this case, the radius values of 0.6 and 0.7 only produce 1 membership function from each input because one cluster center is sufficient to cover all of the dataset. As a result, only one rule is generated in this case while ANFIS learning could be applied to a fuzzy system with a minimum of two rules. On the other hand, a lower radius value leads to a higher number of rules and membership functions in each variable because lower influence of cluster centers. Increasing the number of membership functions would cause a decrease in CVRMSE training since the fuzzy system is more complex and it could produce better output.

Table 5-3 Model I Trials

Trial	Radius	Squash Factor	Accept Ratio	Reject Ratio	Step Size Initial	Increase Rate	Decrease Rate	Epoch	RMSE Model	RMSE Validation	CVRMSE Training	CVRMSE Validation	Remarks
1	0.2	1.5	0.5	0.15	0.1	1.1	0.9	3081	108.79	280.95	13.12%	33.89%	Failed
2	0.3	1.5	0.5	0.15	0.1	1.1	0.9	4008	129.19	206.35	15.58%	24.89%	Failed
3	0.4	1.5	0.5	0.15	0.1	1.1	0.9	5000	114.04	209.98	13.76%	25.33%	Failed
4	0.5	1.5	0.5	0.15	0.1	1.1	0.9	5000	136.25	209.20	16.43%	25.24%	Failed
5	0.6	1.5	0.5	0.15	0.1	1.1	0.9	5000	-	-	-	-	Insufficient Rule
6	0.7	1.5	0.5	0.15	0.1	1.1	0.9	5000	-	-	-	-	Insufficient Rule
7	0.2	1.25	0.5	0.15	0.1	1.1	0.9	44	81.22	279.95	9.80%	33.77%	Failed
8	0.3	1.25	0.5	0.15	0.1	1.1	0.9	520	84.97	260.87	10.25%	31.47%	Failed
9	0.4	1.25	0.5	0.15	0.1	1.1	0.9	466	119.92	205.78	14.46%	24.82%	Pass
10	0.5	1.25	0.5	0.15	0.1	1.1	0.9	160	129.98	204.62	15.68%	24.68%	Failed
11	0.6	1.25	0.5	0.15	0.1	1.1	0.9	5000	-	-	-	-	Insufficient Rule
12	0.7	1.25	0.5	0.15	0.1	1.1	0.9	5000	-	-	-	-	Insufficient Rule
13	0.4	1.5	0.5	0.15	0.4	1.7	0.9	4997	120.80	204.60	14.57%	24.68%	The Most Optimal

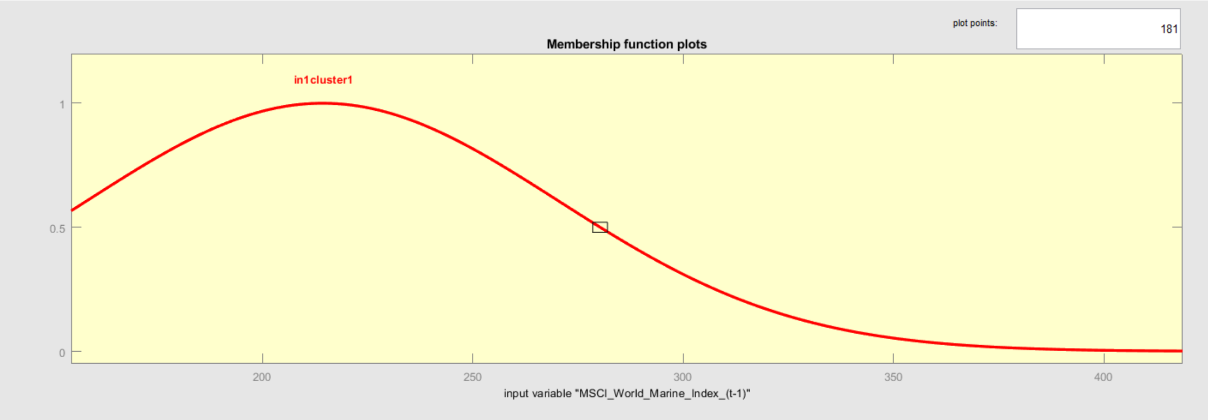

Figure 5-2 Membership Function of MSCI World Marine Index for Trial No. 5

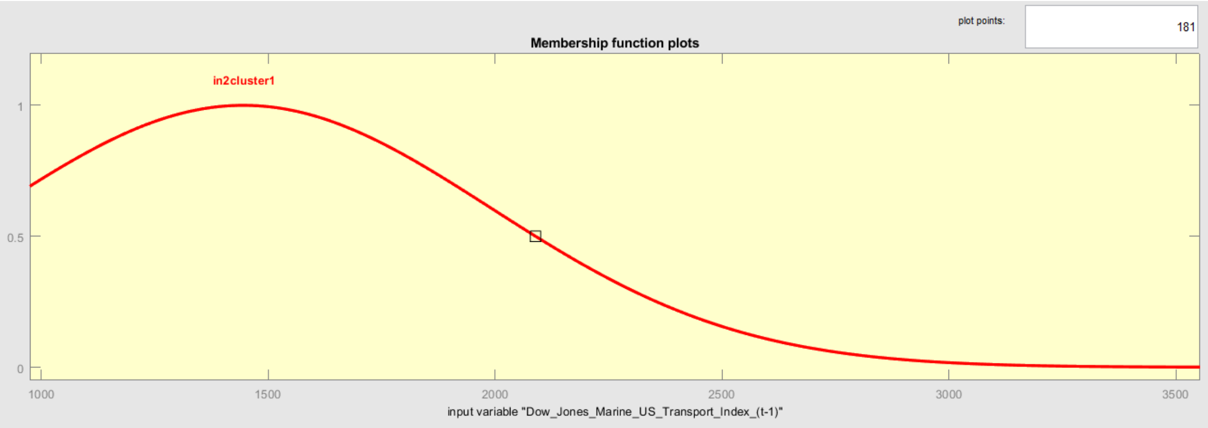

Figure 5-3 Membership Function of Dow Jones Marine US Transport Index for Trial No. 5

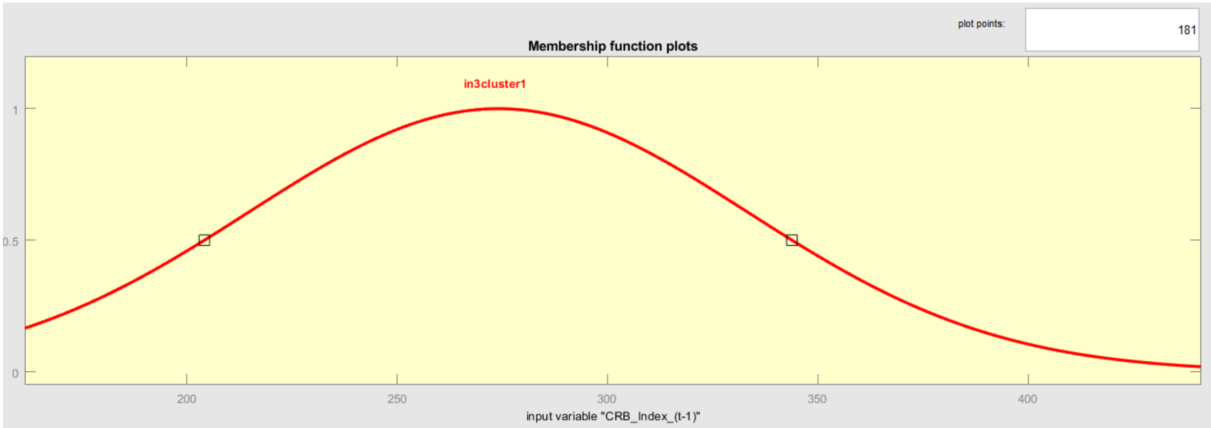

Figure 5-4 Membership Function of CRB Index for Trial No. 5

For example, **Figure 5-2**, **Figure 5-3**, and **Figure 5-4**, 5.3, and 5.4 present that only one membership function from each input is formed, and the only following rule is applied in trial no. 5. Regarding these matters, ANFIS are not able to conduct the learning process.

"If MSCI_World_Marine_Index (t-1) is In1cluster1 and Dow_Jones_Marine_US_Transport_Index (t-1) is in2cluster1 and CRB_Index_(t-1) is in3cluster1 Then BDTI_(t) is out1cluster1."

Once the first step is done and trial no.9 is the sole trial that could pass the first model requirement, the trial model would undergo further optimization. The goals for this further optimization are reducing CVRMSE validation and maintaining CVRMSE training within the first model limitation. After conducting many trials, the process results trial no.13 as the most optimal model.

The resulting model would compete with the other two models and also be optimized with GA (the second model) and PSO (the third model). The model has three membership functions initially (**Figure 5-5**, **Figure 5-6**, and **Figure 5-7**) for each input and the range of each membership function is changed after the model undergoes ANFIS learning (**Figure 5-8**, **Figure 5-9**, and **Figure 5-10**).

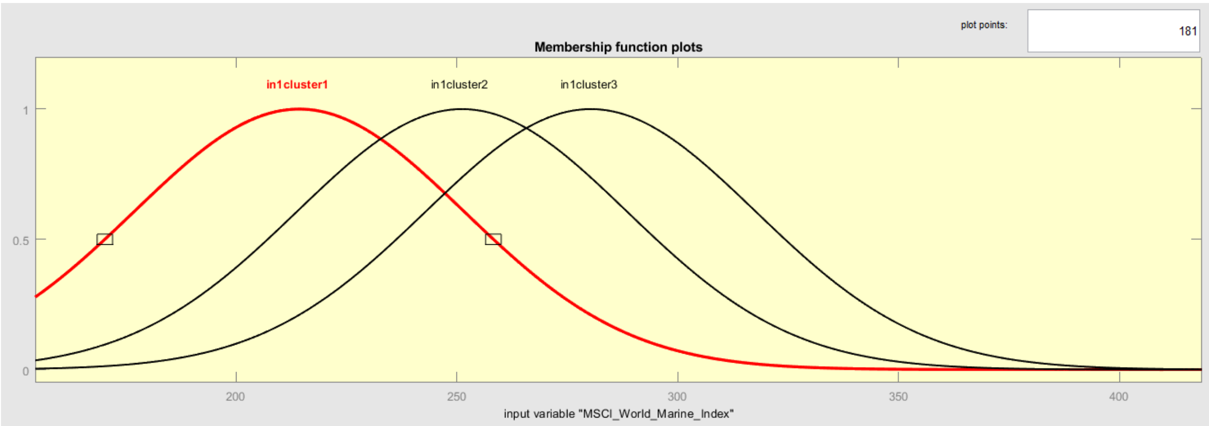

Figure 5-5 Initial Membership Function of MSCI World Marine Index for Trial No. 13

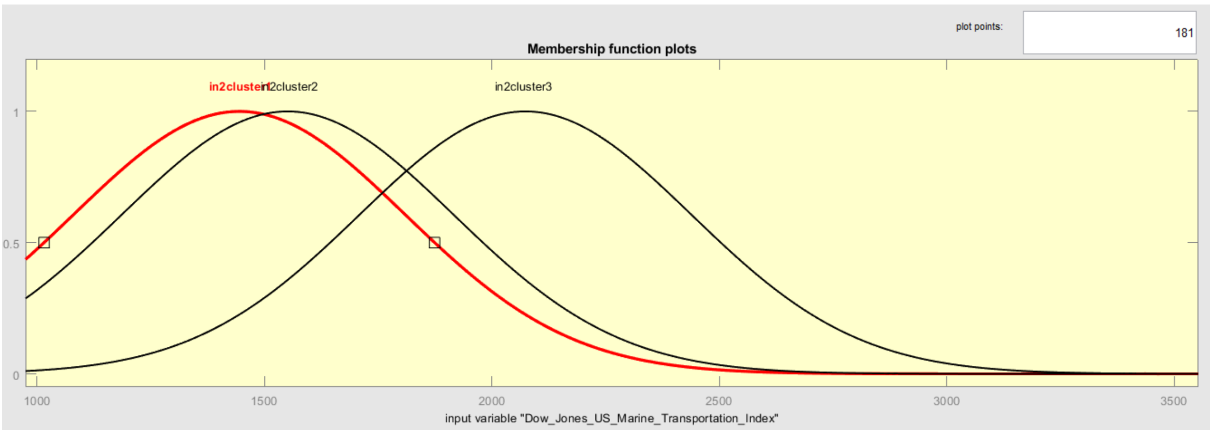

Figure 5-6 Initial Membership Function of Dow Jones US Marine Transportation Index for Trial No. 13

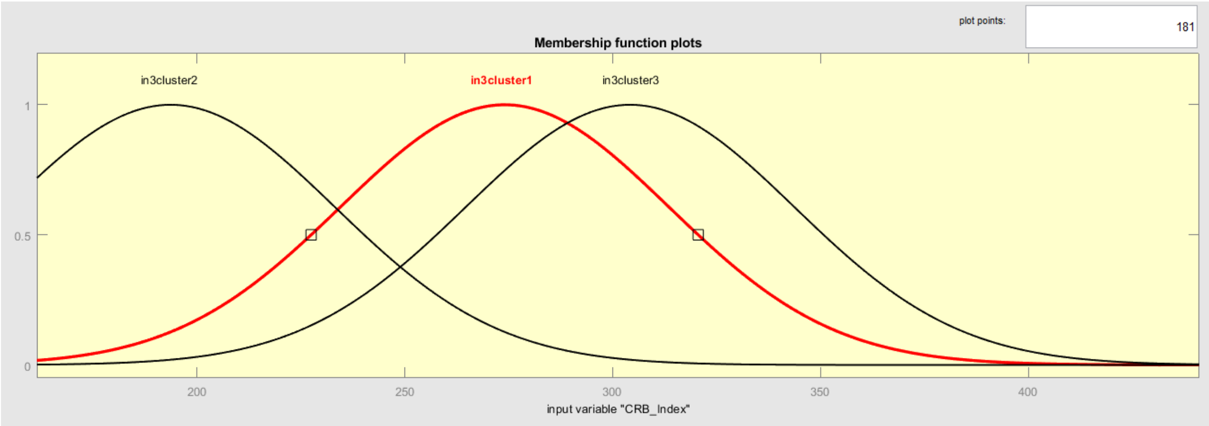

Figure 5-7 Initial Membership Function of CRB Index for Trial No. 13

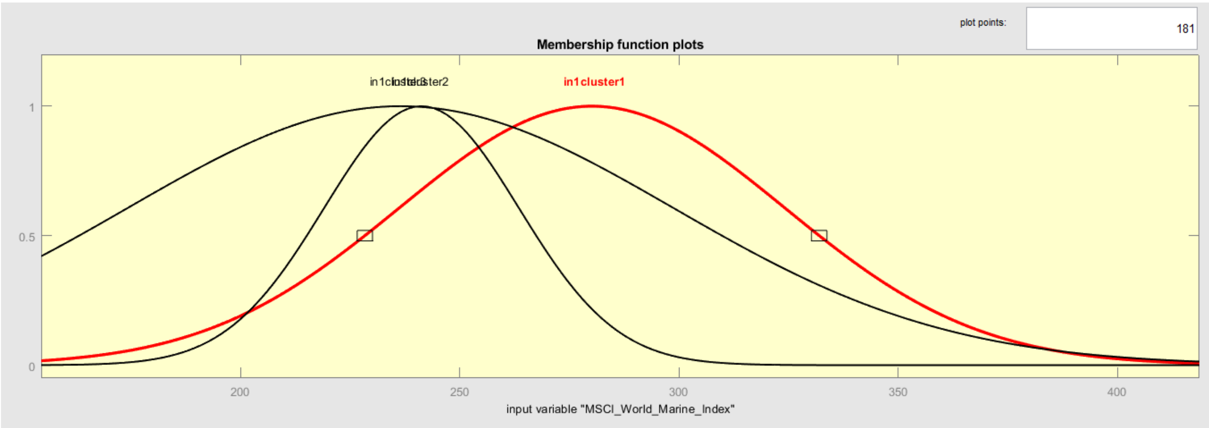

Figure 5-8 Membership Function of MSCI World Marine Index for Trial No. 13 After ANFIS Learning

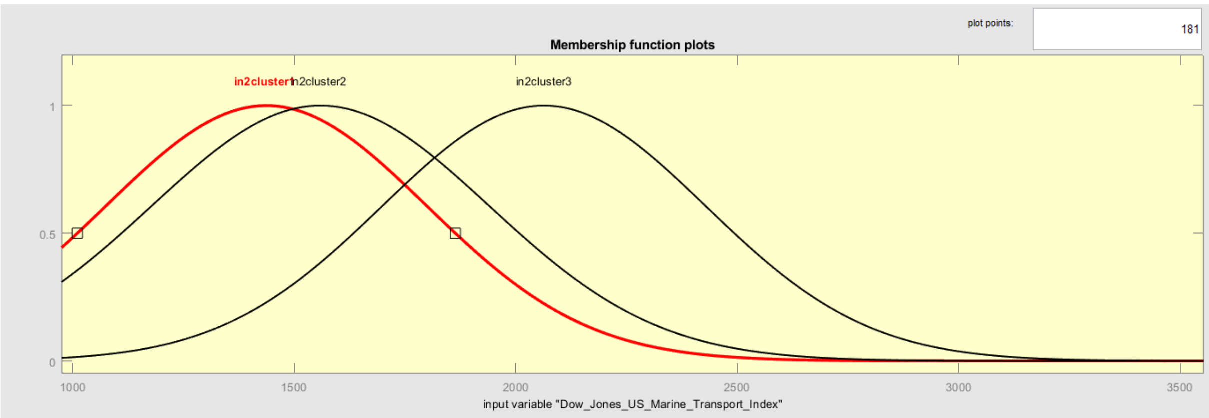

Figure 5-9 Membership Function of Dow Jones US Marine Transportation Index for Trial No. 13 After ANFIS Learning

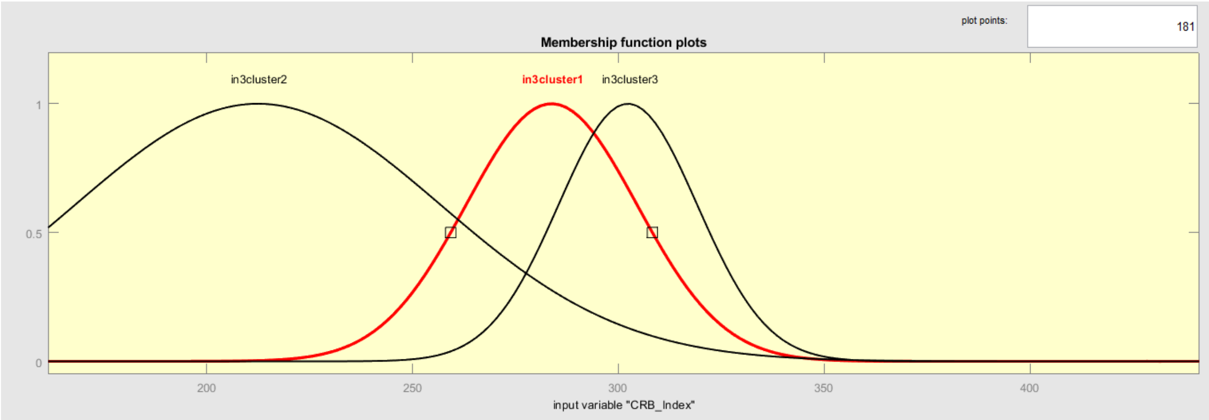

Figure 5-10 Membership Function of CRB Index for Trial No. 13 After ANFIS Learning

The changes also occur in its consequent parameters once the ANFIS learning is done. The model uses **Formula 5.1** which consists of four constants (p,q,r, and s) as it has three inputs (x_1, x_2, and x_3). Nevertheless, the sole changed constant is s (**Table 5-4**) while the constants of p,q, and r are zero in the initial condition and after ANFIS Learning. Also, the rules (**Figure 5-11** ANFIS Rules for trial no. 13 (Model 1)) in this model remain equal during the ANFIS Learning process because ANFIS Learning does not change the rules but antecedent and consequent parameters.

(5.1) $$Fi = p_i x_1 + q_i x_2 + r_i x_3 + s_i$$

Where:

i = 1,2,3

Table 5-4 Consequent Parameter Changes (Model 1)

Variables	S	
	Initial	Learning
Out1cluster1 (i = 1)	150.10	2232
Out1cluster2 (i = 2)	94.35	693.40
Out1cluster3 (i = 3)	-1475	-2869

If	MSCI_World_Marine_Index	is	In1cluster1	and	Dow_Jones_Marine_US_Transport	is	In2cluster1	and	CRB_Index	is	In3cluster1	then	Out1	is	Out1cluster1
			In1cluster2				In2cluster2				In3cluster2				Out1cluster2
			In1cluster3				In2cluster3				In3cluster3				Out1cluster3

Figure 5-11 ANFIS Rules for trial no. 13 (Model 1)

ANFIS – GA (Model 2)

The second model in this research is an experiment to optimize model 1 using genetic algorithms. The methodology part states that selethe ction method, elite count, and crossover fraction are the adjustable parameters during the trials. **Table 5-5** provides trials that are conducted to determine the final form of the second model. The parameters that are input for trial 1 to trial 18 refer to some papers mentioned in the methodology part and they are called initial trials while trial 19 is produced from optthe imization process.

Table 5-5 Trials for the second model

Trial	Selection	Elite count	Crossover Fraction	RMSE Training	CVRMSE Training	CVRMSE Validation
1	Roulette Wheel	0	0.7	120.90	14.82%	25.32%
2	Roulette Wheel	3	0.7	119.13	14.61%	25.25%
3	Roulette Wheel	7	0.7	118.44	14.52%	25.24%
4	Roulette Wheel	0	0.8	119.65	14.67%	25.25%
5	Roulette Wheel	3	0.8	119.18	14.61%	25.24%
6	Roulette Wheel	7	0.8	119.2	14.61%	25.25%
7	Roulette Wheel	0	0.9	129.06	15.82%	26.27%
8	Roulette Wheel	3	0.9	119.01	14.59%	25.24%
9	Roulette Wheel	7	0.9	119.34	14.63%	25.25%
10	Tournament	0	0.7	170.22	20.87%	30.56%
11	Tournament	3	0.7	118.14	14.48%	25.24%
12	Tournament	7	0.7	118.24	14.50%	25.23%
13	Tournament	0	0.8	405154	49675.04%	40345.58%
14	Tournament	3	0.8	118.64	14.55%	25.24%
15	Tournament	7	0.8	118.45	14.52%	25.24%
16	Tournament	0	0.9	639592	78418.97%	66842.04%
17	Tournament	3	0.9	119.35	14.63%	25.25%
18	Tournament	7	0.9	119.36	14.63%	25.25%
19	Tournament	9	0.6	118.07	14.48%	25.24%

To determine the strategy to optimize the model, the effect of parameter changes should be examined while the remaining parameters are constant. The first parameter which is investigated in this model is selection type. The performance of the roulette wheel and tournament selection is compared based on the CVRMSE training and validation in equal numbers of elite count and crossover fractions such as trial 1 versus trial 10 and so on.

Based on the initial trial, the roulette wheel has superior performance over the tournament selection when zero elite count is applied (trials 1,4,7,10,13, and 16). Meanwhile, in higher elite count numbers, the tournament selection is slightly better than the roulette wheel (trials 3,6,12, and 15). Overall, the roulette wheel has more advantages than the tournament selection but the lowest RMSE training is resulted from the selection tournament (trial 11).

Since the roulette wheel is a probability-based method and the tournament is a comparative-based method, the roulette wheel could find the solution quicker but it is usually trapped in a local optima point. On the other hand, the tournament selection has better ability in terms of exploration and it causes the probability of finding the global optima to be higher than the roulette wheel. These are the reasons why the tournament selection is worse than the roulette wheel in zero elite count condition but the minimum resulting RMSE value from the tournament selection is less than the roulette wheel. In this research, the random numbers are generated to provide solutions for minimizing the RMSE training of the model. Each random number is assigned with a fitness value while the fitness function is the RMSE training.

In terms of finding the best solution, the training selection compares n solution (n = 4 in this research) or a set of random number and choose the best ones then pass it to the next generation. The zero number of elite count means that the quantity of individuals that may be assured to successfully reproduce and pass on their genetic material to the subsequent generation is 0. Consequently, all individuals are new in each generation in this condition. In other words, the best individual(s) would not be passed on to the next generations. The roulette wheel could take an advantage in searching time in this condition as the higher fitness value of an individual leads to a greater probability of being chosen. Nevertheless, this condition would be more difficult to apply the tournament selection since it would take more time or more generation numbers to explore the solutions. The high randomness of population quality that is resulted from mutation and crossover would raise problems as well.

Regarding the conditions, the elitism is needed to be included in terms of finding the optimal solution for the model. Besides the elitism, the crossover individuals have a significant role in maintaining part of the characteristics of the previous generations to the next generations. The proportion of individuals in the subsequent generation, excluding offspring from the elite group, that are generated through the process of crossover could be adjusted by the crossover fraction. For instance, 7 of 150 individuals are the elite ones while approximately 114 and 29 individuals are resulted from the crossover and mutation process in trial 15.

Due to the tournament selection chosen in the further optimization, trials 11,12,14,15,17, and 18 need to be assessed to determine the combination number between the crossover fraction and elite count. Regarding the trials, increasing the crossover percentage and maintaining the number of elite counts in the population provide a slightly less accurate model. On the other side, an increase in the elite count without changing the crossover fraction leads to the the same results except when the crossover fraction is set to 0.8. In contrast, a promising result is given when trials 12 and 14 are compared. Regarding this comparison, a rise in the elite count number and a reduction in crossover fraction could generate a better model. Balancing the number of elite counts and crossover is an important thing in the genetic algorithm tuning because of two reasons. Firstly, avoiding the excessive number of mutations in a population has a significant role in keeping the randomness of generation at the proper level. Secondly, passing the best characteristics from the previous generation to the next one could be a safety net to ensure the quality of solutions from each generation. Since trial 11 has the lowest RMSE training, it is chosen as the basis of further optimization. Then, after several trials are conducted, trial 19 is considered as the most optimal model for the ANFIS – GA BDTI predictor.

Trial 19 has different membership functions and consequence parameters from the classical ANFIS model because of the GA tuning. In the antecedents part, the range of the membership functions are changed (**Figure 5-12**, **Figure 5-13**, and **Figure 5-14**) and the components of p,q, and r are not zero anymore. Also, the constant of s is adjusted by the algorithm (**Table 5-6** Consequent Parameters of the Model 2). The fuzzy rules in this model are not changed because one of Sugeno fuzzy characteristics is that as long as the number of membership functions is constant, the rules remain the same. Since the genetic algorithms only execute tuning tasks in this model, the number of membership functions would not be modified.

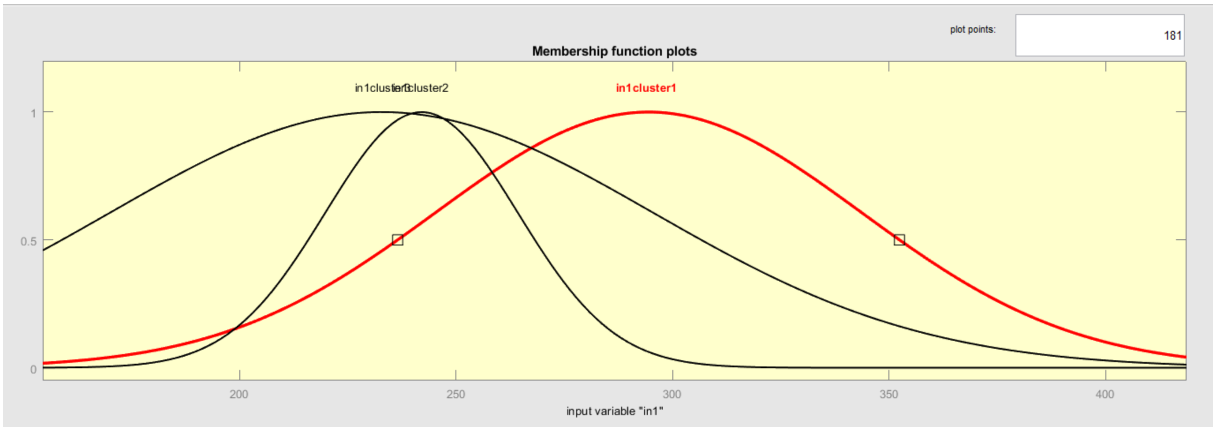

Figure 5-12 Initial Membership Function of MSCI World Marine Index for Trial No. 19 (Tuned by GA)

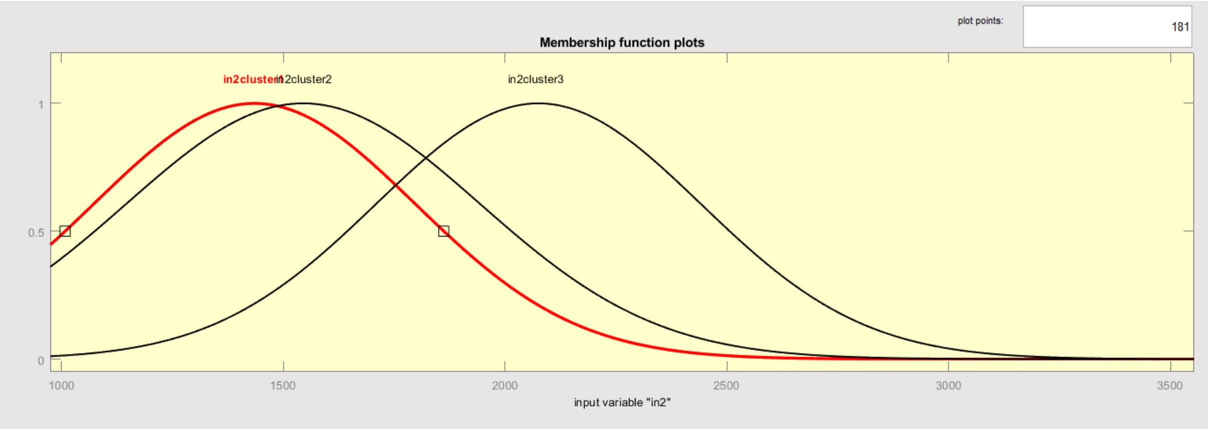

Figure 5-13 Membership Function of Dow Jones US Marine Transportation Index for Trial No. 19 (Tuned by GA)

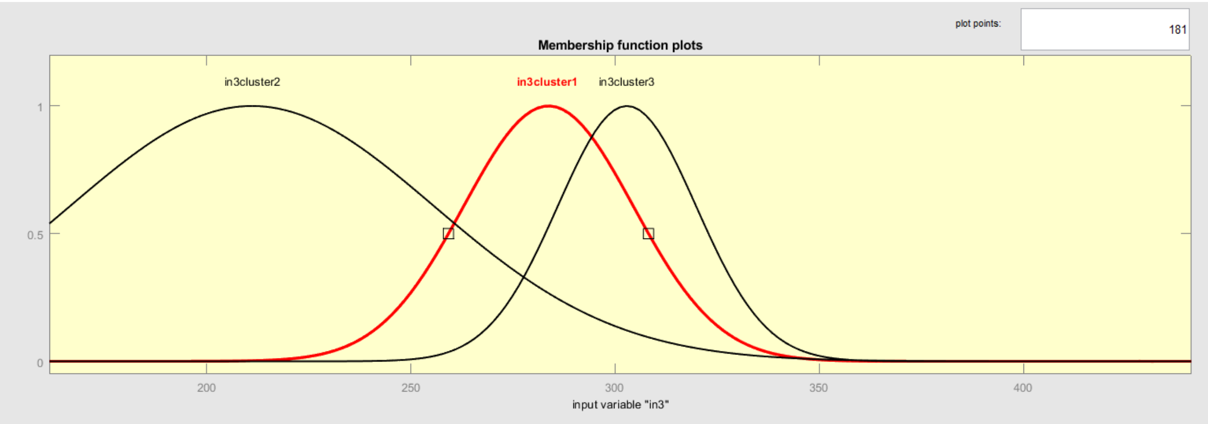

Figure 5-14 Membership Function of CRB Index for Trial No. 19 (Tuned by GA)

Table 5-6 Consequent Parameters of the Model 2

Variables	p	q	r	S
out1cluster1 (i = 1)	-2.54	1.033	-7.394	2231
out1cluster2 (i = 2)	0.558	0.43	-3.72	694.80
out1cluster3 (i = 3)	0.1033	-0.05852	11.74	-2869

ANFIS -PSO (Model 3)

In the last model, the membership functions and consequent parameters are tuned by Particle Swarm Optimization. As explained in the methodology section, the parameters of swarm size, self-adjustment weight, and social adjustment weight are not constant during trials to generate the most optimal ANFIS – PSO model. **Table 5-7** shows the trials list using parameters from several papers (trials 1 – 10) and the most optimal model (trial 11) after several trials using many numbers for weight and iterations. In this research, similar to the previous model, the main goal of the PSO tuning is updating membership functions and consequences parameters in order to minimize RMSE training.

Table 5-7 Trials for The Third Model

Trial	Self Adjustment Weight	Social Adjustment Weight	Population Size	RMSE Training	CVRMSE Training	CVRMSE Validation
1	2	2	50	118.78	14.42%	25.23%
2	1	2	50	118.77	14.41%	25.22%
3	0.5	1	50	117.62	14.27%	25.22%
4	1.49	1.49	50	118.77	14.41%	25.22%
5	1.7	1.7	50	118.77	14.41%	25.22%
6	2	2	100	118.84	14.42%	25.23%
7	1	2	100	118.77	14.41%	25.22%
8	0.5	1	100	117.61	14.27%	25.23%
9	1.49	1.49	100	118.77	14.41%	25.22%
10	1.7	1.7	100	118.77	14.41%	25.22%
11	0.25	0.25	150	115.03	13.96%	25.22%

Trial 1 – Trial 10 shows that the RMSE trainings are slightly equal with certain numbers of self and social adjustment weights regardless of their population size. The main reason for this condition is the weight numbers are quite high. Regarding **Formula 3.12**, the higher numbers of weights produce faster particle movement within the search space then the convergence rate is faster during solution searching and it only needs a lower number of iterations. **Figure 5-15** confirms the circumstances. In several cases, the solution-finding process is stopped in local optima therefore it results in a non-optimal model. Based on their resulting RMSE training and progress during the learning process, their position could be assumed in the local optima points.

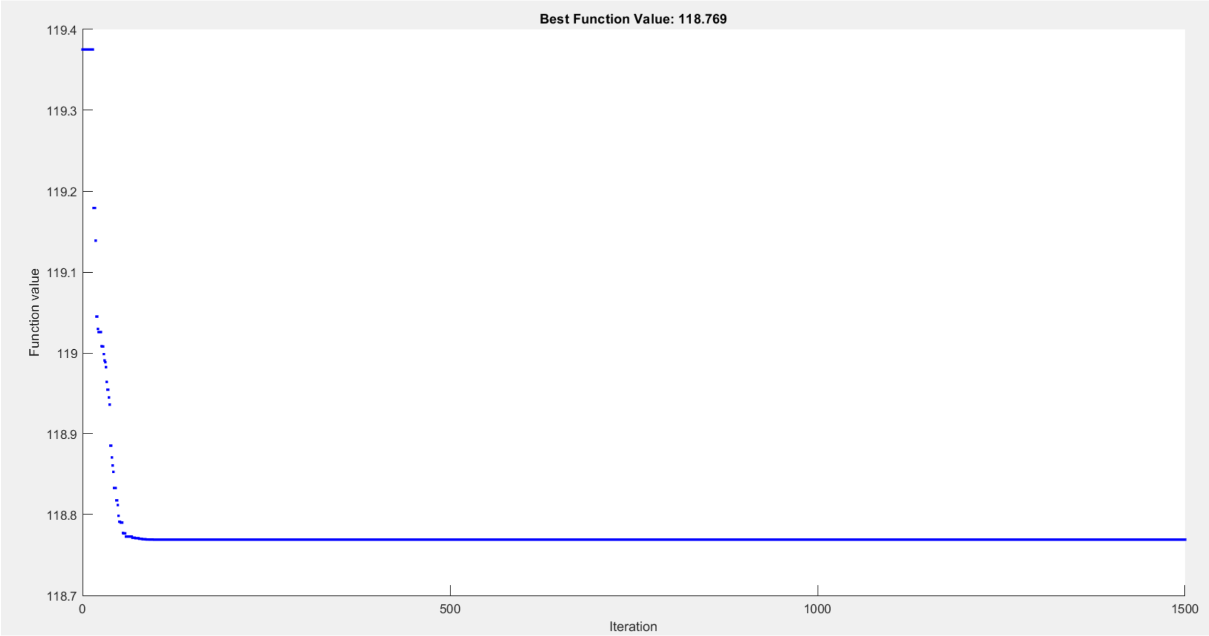

Figure 5-15 Learning Curve for Trial 4 (Model 3)

To find a lower RMSE, a further optimization process should be conducted. The first step is defining the 'low' number of weights for this model. Since trial 8 has the lowest RMSE training among trials 1 to 10, its weights could be utilized as the basis. Nevertheless, the weight value of 1 does not generate good RMSE values in other trials, trial 8's self-adjustment weight value (0.5) is considered as the starting and maximum number for the further process.

In addition, the patterns of self-adjustment and social adjustment weight are that they have equal value or the self-adjustment is lower than social adjustment with the ratio of 1:2 based on the papers suggestion and the patterns are used in the next further step. Because **Figure 5-15** presents a huge number of useless iterations, the swarm size is also adjusted to provide more solutions and optimize the maximum iterations parameter (1500). Finally, after several trials, trial 11 is proposed to compare its performance with the other models.

The best model of ANFIS–PSO in this research uses the equal number for its self-adjustment and social adjustment weight. Theoretically, the equal combination is the best one while the lower self-adjustment value than the social adjustment could reduce the exploration ability of individual particle and the lower social adjustment would make the particle fly aimlessly. The equal numbers could provide a good balance and the final position of the particle would be the average between the personal and social/global best position (Engelbrecht, 2007).

In terms of iteration utilization, trial 11 utilizes all of the iteration process to learn which is shown in **Figure 5-16**. Trial 11 also uses the same rules with the classical and ANFIS – GA models for its fuzzy system while some of its membership and consequences parameters are different from the other models. The first type parameters can be seen from the membership function form in **Figure 5-17, Figure 5-18**, and **Figure 5-19** while the last type parameters are shown in **Table 5-8**.

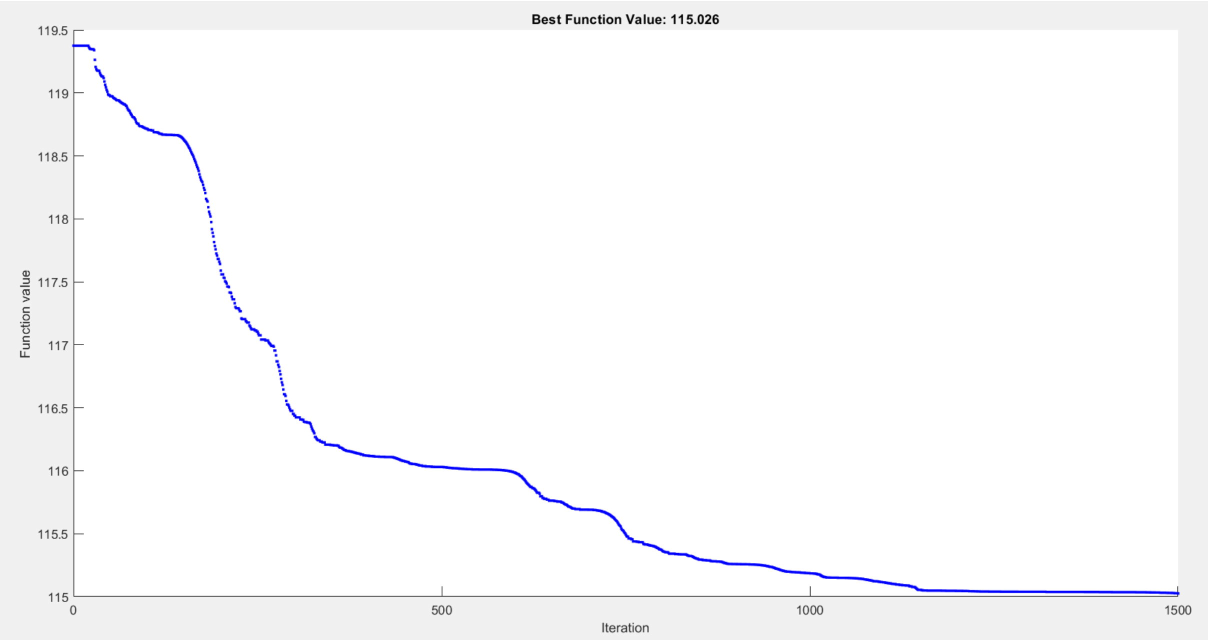

Figure 5-16 Learning Curve for Trial 11 (Model 3)

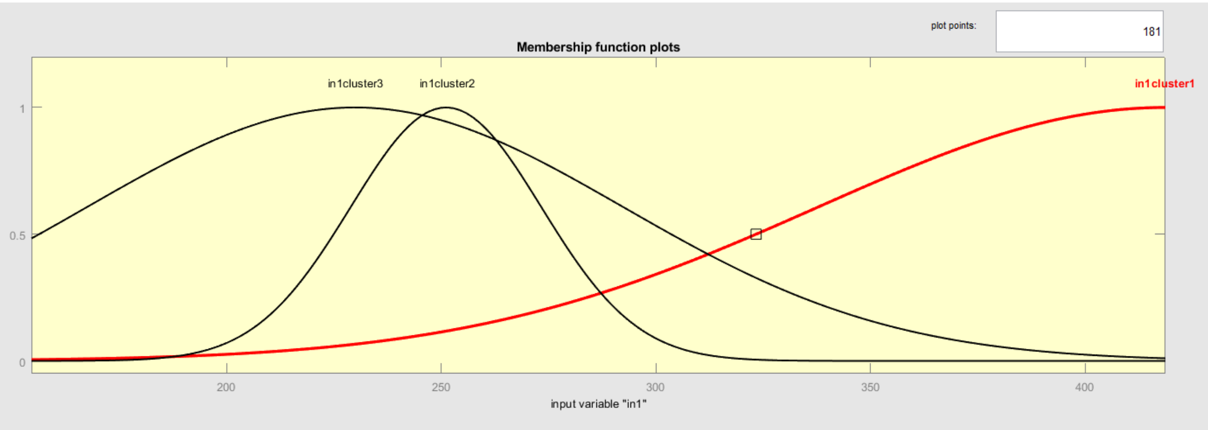

Figure 5-17 Initial Membership Function of MSCI World Marine Index for Trial No. 11 (Tuned by PSO)

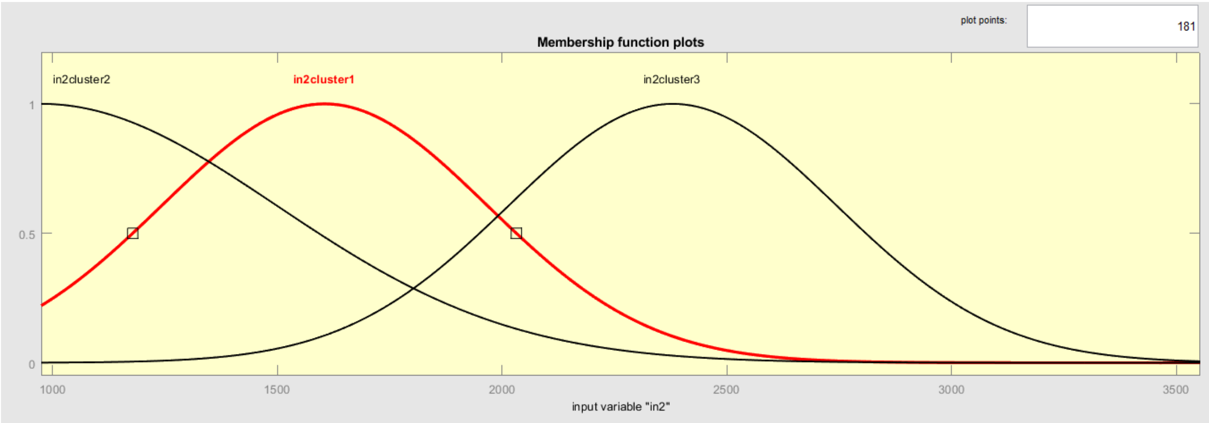

Figure 5-18 Initial Membership Function of Dow Jones US Marine Transportation Index for Trial No. 11 (Tuned by PSO)

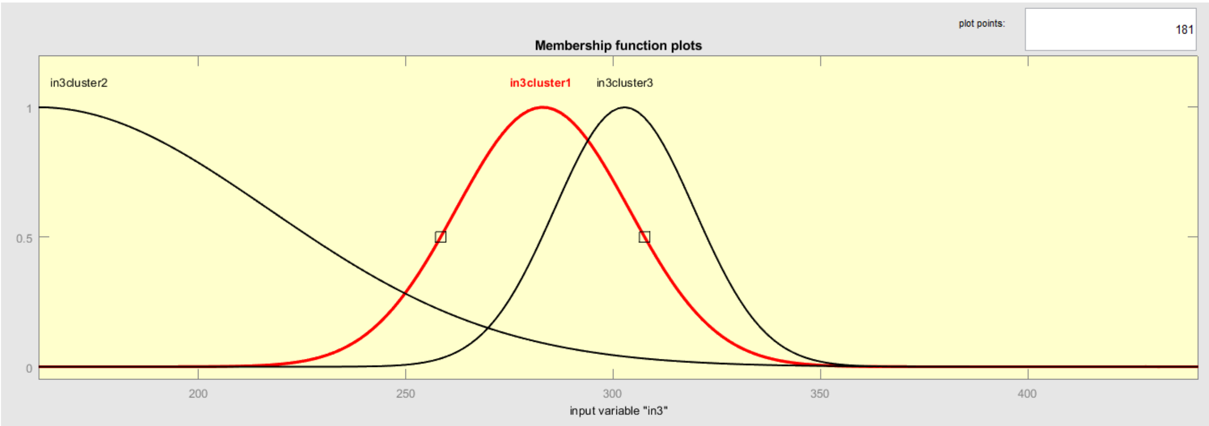

Figure 5-19 Initial Membership Function of CRB Index for Trial No. 11 (Tuned by PSO)

Table 5-8 Consequent Parameters of the Model 3

Variables	p	q	r	S
out1cluster1 (i = 1)	-2.54	1.389	-7.396	1741
out1cluster2 (i = 2)	0.5573	0.43	-3.721	697
out1cluster3 (i = 3)	0.1032	-0.05857	11.74	-2869

5.3. Models Comparison

Rather than seeking the global optimal solution, this thesis aims to identify an acceptable optimal solution for each model due to the tendency of the global optimal solution to decrease the root mean square error (RMSE) during training, while simultaneously increasing the RMSE during validation. Put simply, the model may become overfit or fail to generalize to data from different time periods. Regarding the ability of each model to follow the actual trendline, each model could follow the trend properly as shown by **Figure 5-20** (Model 1), **Figure 5-21** (Model

2), and **Figure 5-22** (Model 3) in the period of January 2008 to June 2017 (Training data). In terms of their coefficient determination, only slightly below 20% of the actual BDTI variation could not be explained by the prediction results of each model (**Table 5-9**).

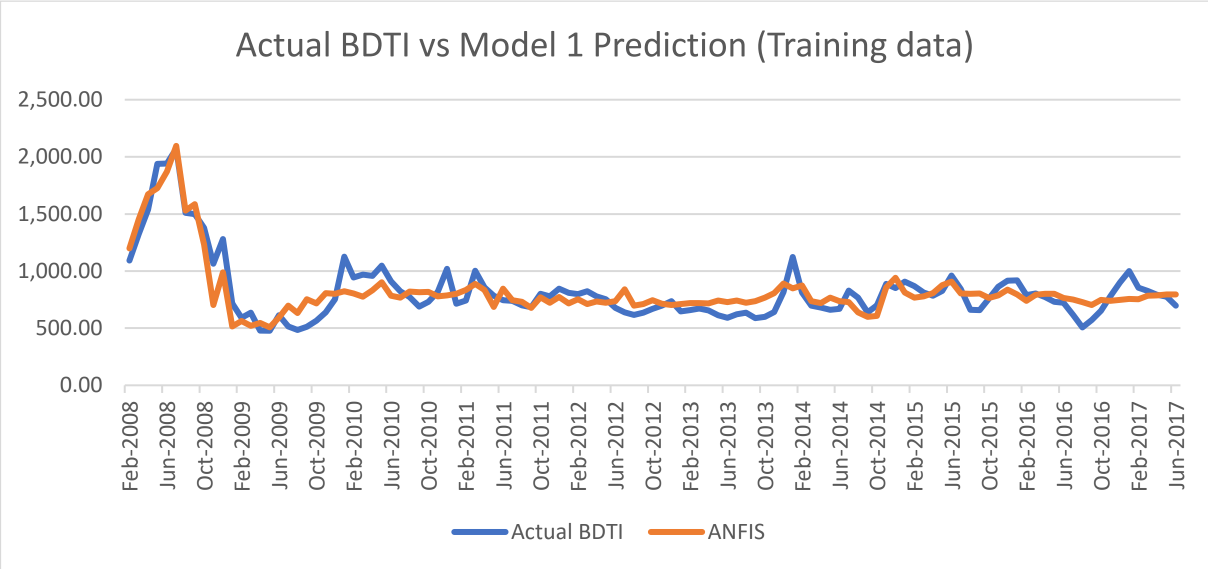

Figure 5-20 Comparison of The Actual BDTI and The ANFIS Model Training Result

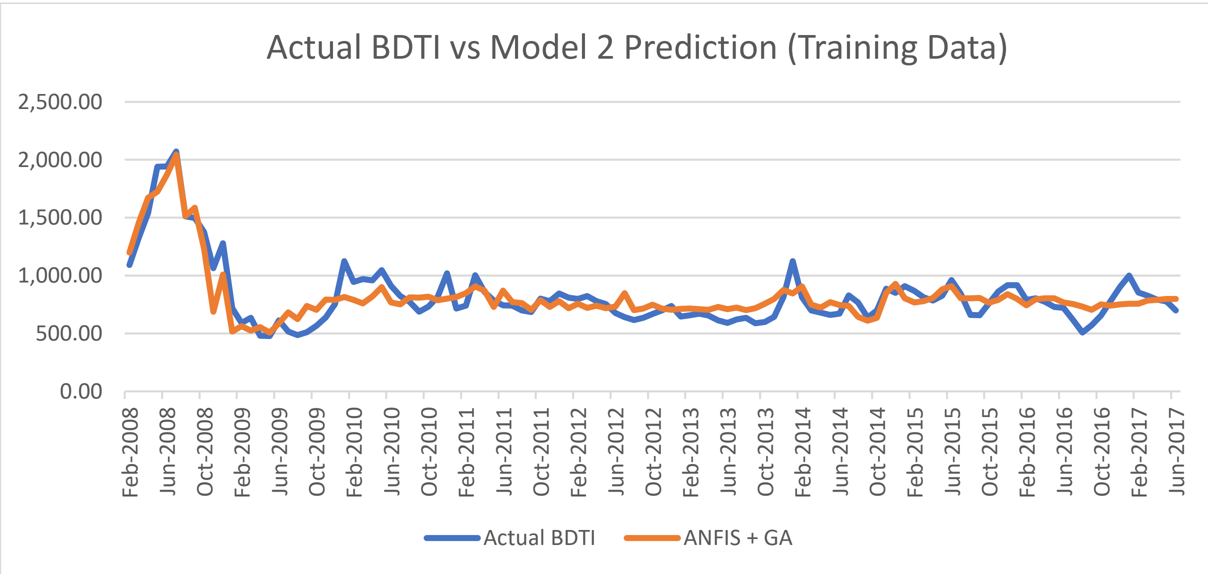

Figure 5-21 Comparison of The Actual BDTI and The ANFIS + GA Model Training Result

Table 5-9 R^2 of the Model results and The Actual BDTI in The Training Data Period

Model	Algorithms	Coefficient of Determination
1	ANFIS	0.82
2	ANFIS-GA	0.82
3	ANFIS-PSO	0.83

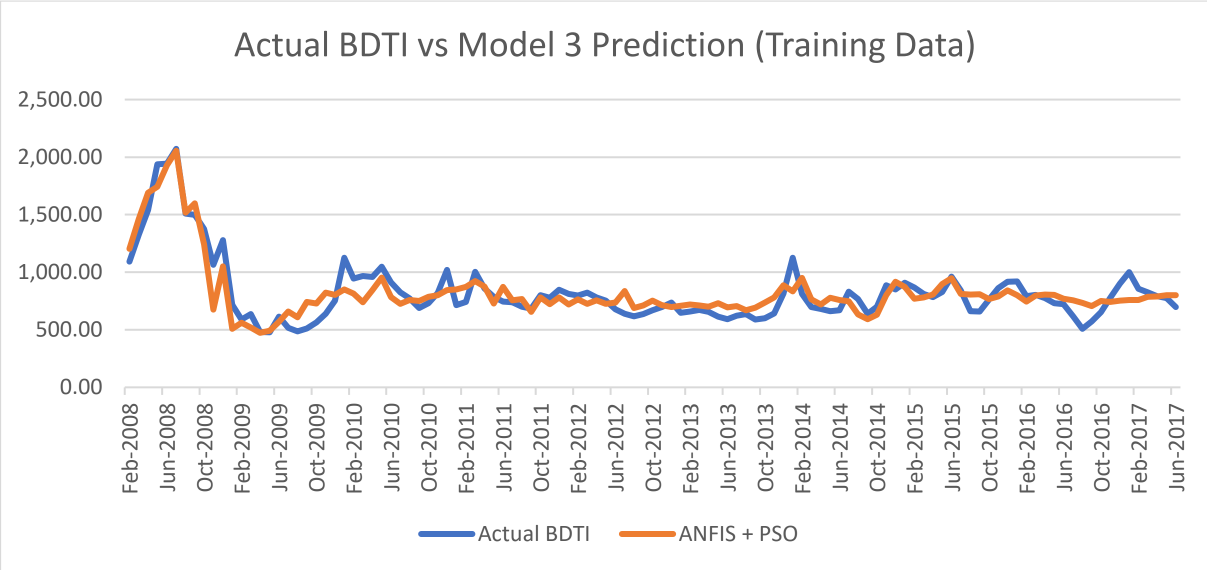

Figure 5-22 Comparison of The Actual BDTI and The ANFIS + PSO Model Training Result

Meanwhile, the performance of the model to accommodate the validation data period (July 2017 – December 2019) is quite different from the performance in accommodating training data. In this simulation, the prediction results from each model using validation data input explain only around 8% of the actual BDTI variation (**Table 5-10**). **Figure 5-23**, **Figure 5-24**, and **Figure 5-25** present the comparison between the models output and the actual BDTI values in the validation data period.

Table 5-10 R^2 of the Model results and The Actual BDTI in The Validation Data Period

Model	Algorithms	Coefficient of Determination
1	ANFIS	0.083
2	ANFIS-GA	0.083
3	ANFIS-PSO	0.084

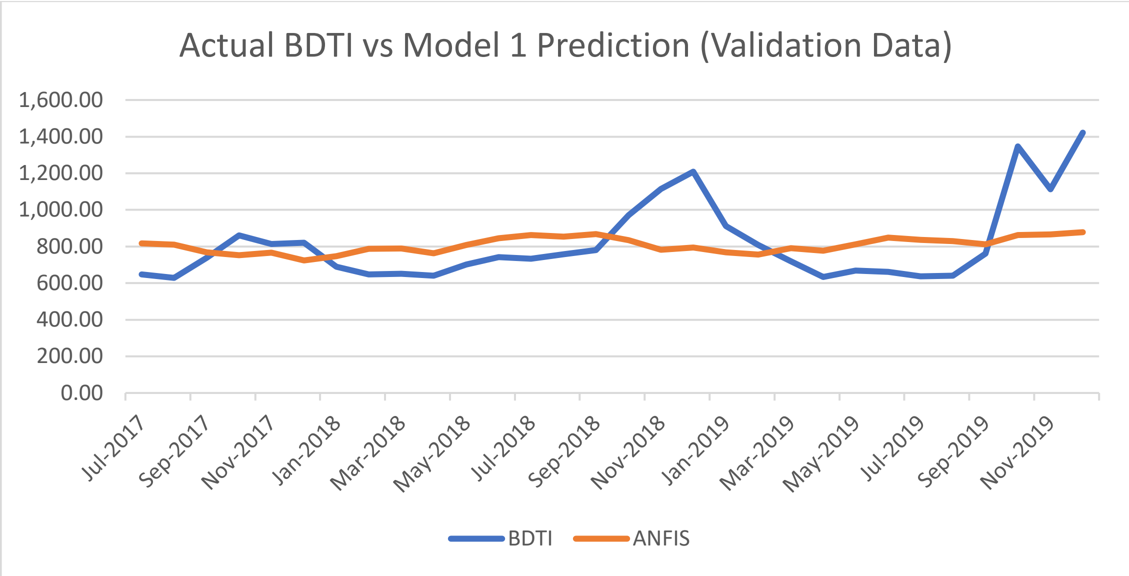

Figure 5-23 Comparison of The Actual BDTI and The ANFIS Model Validation Results

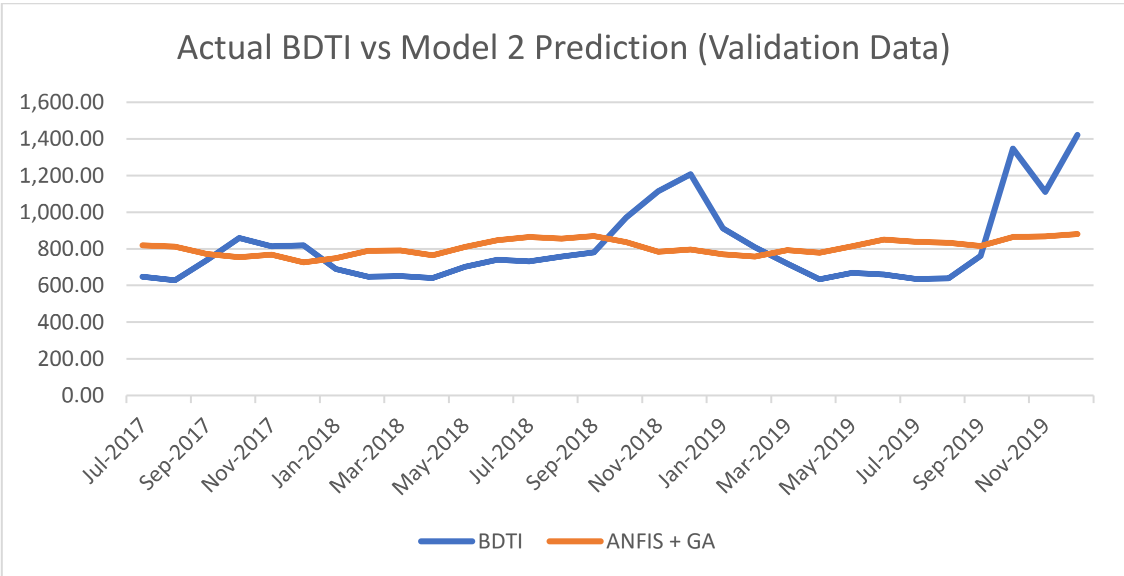

Figure 5-24 Comparison of The Actual BDTI and The ANFIS + GA Model Validation Results

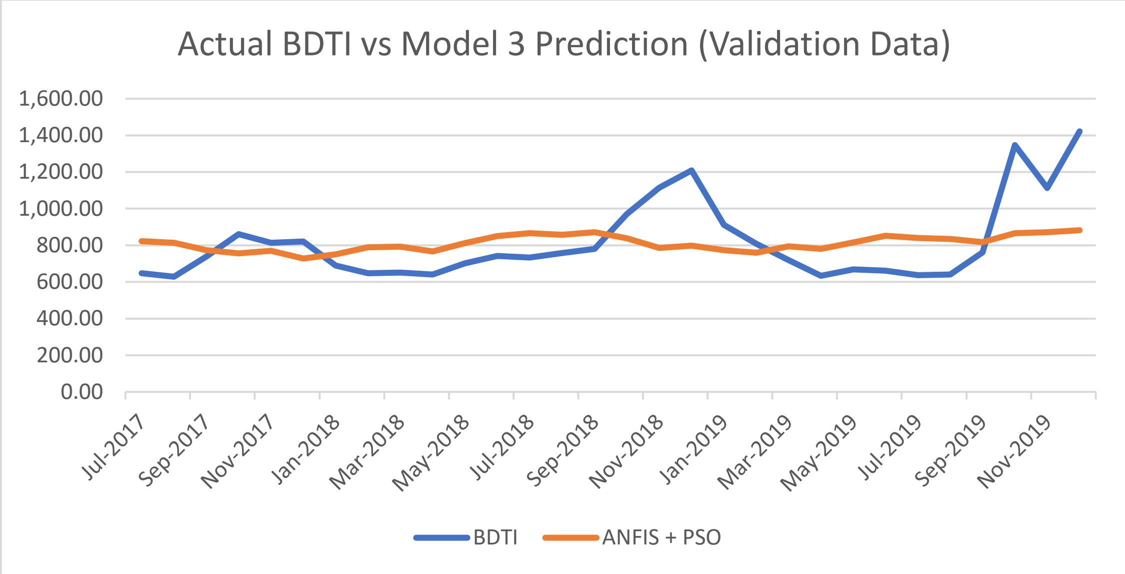

Figure 5-25 Comparison of The Actual BDTI and The ANFIS + PSO Model Validation Results

The disparity in performance of the models in handling training and validation data can mostly be attributed to variations in the most influential elements across different time periods. **Table 5-11** shows the coefficient relationship between the input candidates and output. In training data, same as in the overall data, the MSCI World Marine Index, Dow Jones Marine US Transport Index, and CRB Index are the most significant factors in determining the BDTI. Nevertheless, the Dow Jones Marine US Transport Index, SSECI, and Gold Price have the highest R values in the validation data period. Based on their values and the duration from each period, It could be concluded that the main determinant factors of BDTI are different in the long-term and short-term periods.

Table 5-11 R Coefficient Comparisons

Variables	Overall	Training Data	Validation Data
Brent Oil	0.21	0.23	0.06
ARCA Oil	0.23	0.26	-0.01
S&P 500 Vol index	0.10	0.10	0.15
Dow Jones Marine US Transport Index	0.71	0.76	0.24
MSCI World Marine Index	0.60	0.70	-0.19
SSECI	0.24	0.31	-0.40
Gold Price	-0.34	-0.40	0.32
CRB	0.42	0.52	-0.02

Regarding the accuracy and error metrics, all of the model meet the required values proposed by Walker (2019) of CVRMSE and MAPE which are showed by **The ANFIS** model, which has been fine-tuned using PSO methods, demonstrates higher performance in both the validation and training phases, with the exception of the MAE and MAPE parameters in the validation stage. One notable finding from this study is that the application of Particle Swarm Optimization (PSO) tuning yielded a greater reduction in the Root Mean Square Error (RMSE) for training (115.03) compared to the reduction achieved by Genetic Algorithm (GA) tuning (118.07). Additionally, the PSO tuning approach also resulted in a superior RMSE for validation compared to the GA tuning approach.

Table 5-12. The ANFIS model, which has been fine-tuned using PSO methods, demonstrates higher performance in both the validation and training phases, with the exception of the MAE and MAPE parameters in the validation stage. One notable finding from this study is that the application of Particle Swarm Optimization (PSO) tuning yielded a greater reduction in the Root Mean Square Error (RMSE) for training (115.03) compared to the reduction achieved by Genetic Algorithm (GA) tuning (118.07). Additionally, the PSO tuning approach also resulted in a superior RMSE for validation compared to the GA tuning approach.

Table 5-12 Accuracy Metrics from Each Model

Training						
Model	RMSE	CVRMSE Req.	CVRMSE	MAE	MAPE Req.	MAPE
ANFIS	120.80	30%	14.57%	97.20	20%	12.54%
ANFIS - GA	118.07		14.33%	95.68		12.30%
ANFIS - PSO	115.03		13.96%	91.87		11.83%
Validation						
Model	RMSE	CVRMSE Req.	CVRMSE	MAE	MAPE Req.	MAPE
ANFIS	204.60	30%	24.68%	164.91	20%	19.20%
ANFIS - GA	205.83		25.24%	165.60		19.35%
ANFIS - PSO	205.72		25.22%	165.89		19.41%

The results are in line with Wihartiko et al. in 2018. He stated that the PSO could help the model reach the optimal solution while the GA could assist the model in achieving the near-optimal solution. The main characteristic of PSO which is the direct selection approach helps this algorithm to find the solutions better than GA in this research. The characteristic is different from the Genetic Algorithm where the population engineering occurs through the mutation and crossover process and it would lead to saturation at certain iterations to develop its performance. This characteristic also supports PSO as one of the easiest optimization methods to be implemented.

Chapter 6. **Conclusion and Recommendation**

6.1. Conclusion

Oil as one of the most established energy resources is widely consumed in all countries. It could be converted into fuel, cosmetics as well as chemical products. Nevertheless, not all countries could fulfill their oil need by themselves, while some other countries could produce oil excessively. As a result, oil distribution has a significant role in terms of economic development. BDTI or Baltic Dirty Tanker Index is the one of references to determine the freight rate for crude oil tankers. This is because the index is formed from several main tanker routes in the world. Estimating the index could help the tanker companies to determine business plans. Christodoulopoulos in 2019 and Diakodimitris in 2020 suggested Artificial Neural Network as an approach to forecast freight rates. While ANN has some disadvantages, especially in achieving a global optima point due to its learning method, it is combined with a fuzzy system to accommodate the difficulties in a system which is called ANFIS. In order to improve the system performance, some parameters of ANFIS are tuned by Genetic Algorithms and Particle Swarm Optimization then the final model of each algorithm is compared with the other models. In this research, the ANFIS – PSO algorithm is the most superior algorithm to predict BDTI.

6.2. Answers to The Research Sub and Main Questions

This section consists of the answers to sub and main research questions. Initially, the sub-research questions answers are provided and then the last part of this section presents the summary of all sub-research questions answers in order to address the main question.

1st Sub-Research Question :

What are the factors that affect Baltic Dirty Tanker Index?

Answer :

Several factors are identified to provide a choice of the model input. This research refers to several related papers (including factors affecting similar indexes such as the Baltic Dry Tanker Index) and then considers them. This research also proposes some factors to be combined with the references' input. Next, the statistical test is conducted to find the relationship between the factors and BDTI through the coefficient of coefficient correlation.

Based on their coefficient correlation, this research divides the model inputs into two types. The first type is the ones that have a significant influence in long-term periods (overall and training data). Members of the first group are the MSCI World Marine Index, Dow Jones Marine US Transportation Index, and CRB index. Meanwhile, the Dow Jones Marine US Transportation

Index, SSECI, and gold price are the most significant factors in the short-term period (Validation data).

2nd Sub-Research Question :

Which are the most optimum parameters for the ANFIS original model that could be used to forecast the Baltic Dirty Tanker Index using the given inputs?

Answer :

The research defines the optimum for the original ANFIS model as achieving CVRMSEs of 25% and 15% for the training and validation phases, respectively. The primary purpose of this condition is to mitigate the occurrence of overfitting, a prevalent phenomenon in machine learning. The original ANFIS model employs the subtractive clustering approach for the purpose of generating the first FIS. The clustering procedure is characterized by the following ideal parameters: 0.4 for the ra parameter, 1.5 for the squash factor, 0.5 for the accept ratio, and 1.5 for the reject ratio. The aforementioned procedure yields three cluster centers from the given data which are presented by **Table 6.1**.

Table 6-1 Initial Cluster Centers of Model 1

Cluster No.	Date	BDTI	MSCI World Marine Index	Dow Jones US Transport Index	CRB Index
1	Nov-2009	639.38	214.26	1444.71	274.00
2	Mar-2014	698.43	280.28	2073.68	304.17
3	Feb-2017	854.70	251.13	1550.84	193.59

The cluster centers become the center of membership functions in the initial FIS for the input and ANFIS updates the cluster centers, range of membership functions (measured by σ) as well as consequent parameters. The most optimal model is obtained with the following ANFIS learning parameters.

- Initial step size: 0.4
- Step size increase rate: 1.7
- Step size decrease rate: 0.9

All of the clustering and learning parameters are obtained from papers and random number after conducting several trials. Finally, the learning process generates membership function and consequent parameters as shown in **Table 6.2** and **Table 5.4**.

Table 6-2 Membership Function Parameters of Model 1

Input	Membership Function	σ	Center
MSCI World Marine Index	in1cluster1	44.02	280.2
	in1cluster2	22.22	241.3
	in1cluster3	62.28	236.5
Dow Jones US Transport Index	in2cluster1	362.4	1437
	in2cluster2	381.3	1559
	in2cluster3	365	2064
CRB Index	in3cluster1	20.81	283.8
	in3cluster2	44.49	212.4
	in3cluster3	16.88	302.3

3rd Sub-Research Question :

How is the performance of ANFIS models after it is optimized by Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)?

Answer :

Both the genetic algorithm (GA) and particle swarm optimization (PSO) tuning methods demonstrate improved performance in training data and over a long-term period when applied to the ANFIS classical model. This improvement is measured by evaluating the root mean square error (RMSE), coefficient of variation of RMSE (CVRMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). However, there is a discrepancy between the performance of their data processing in the validation phase and the original ANFIS model. The primary determinant of this issue is the diverse array of elements that exert substantial influence throughout both the immediate and extended timeframes, as outlined in **Table 5-11** R Coefficient Comparisons. In light of the restrictions outlined by Walker et al. in 2019, it may be argued that all of the models employed can be characterized as realistic models in this study.

Main Question:

How accurate of ANFIS to predict the Baltic Dirty Tanker Index?

Answer:

The ANFIS models, including those modified by GA and PSO, demonstrated sufficient accuracy in predicting BDTI within the scope of this research. The models have been intentionally built to possess a level of accuracy that is not unduly high, with the aim of mitigating the risk of overfitting. Ensuring the precision of models at a realistic threshold and including a diverse variety of data is of utmost significance. The present study generates ANFIS models that exhibit a range of CVRMSE values between 13.96% and 14.57% for training data along with 24.68% and 25.24% for validation data. Additionally, the mean absolute percentage errors (MAPEs) of the models fall within the range of 11.83% to 12.54% for the long-term period, and approximately 19% for the short-term period. With respect to the constraint, all of the numerical values remain within the permitted range. On the other words, the models shows its superiority to predict BDTI in the long-term period.

6.3. Limitation of The Research

Although the research yields encouraging findings, it is important to acknowledge that there are certain limitations inherent in the study. The data utilized for modeling and validating the models span from January 2008 to December 2019. Put simply, the models used in this research do not account for any alterations in the determining factors that go beyond its scope. One further constraint pertains to the utilization of data on a monthly basis. This implies that the models are unable to capture the fluctuations in data that occur at short sampling intervals. Consequently, the capabilities of the models are constrained solely to monthly fluctuations. Furthermore, the models are limited in their ability to accurately depict the actual conditions due to the constraints on the input numbers. Finally, the temporal constraint imposed on this research results in a restricted number of trials for each model, as certain learning parameters necessitate the execution of a trial-and-error procedure involving random numbers.

6.4. Recommendation for Further Researches

There exist potential enhancements that could be implemented to augment the efficacy of the BDTI predictor. One potential suggestion is to expand the temporal range of the data used for training the model. This would enable the model to capture a greater variety of patterns in the movement of BDTI values. In relation to the employed methodologies, alternative clustering techniques such as grid partitioning, as well as validation approaches like K-fold cross-validation, could be incorporated to enhance the precision level. The alternative approach of utilizing Ant Colony Optimization could also be explored in order to direct the models towards the desired optimal point. Because of the different influence factors in long-term and short-term periods, it would be better to separate the model for predicting BDTI in each period.

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B. Appendices

The First Model Coding

```
clc
clear
trainput = xlsread('C:\Mainkan\Maritime Economics and
Logistics EUR\16. Thesis\Thesis Draft\Data\input output
statistics 2019.xlsx',2,'C2:E114');
traoutput = xlsread('C:\Mainkan\Maritime Economics and
Logistics EUR\16. Thesis\Thesis Draft\Data\input output
statistics 2019.xlsx',2,'B3:B115');
valinput = xlsread('C:\Mainkan\Maritime Economics and
Logistics EUR\16. Thesis\Thesis Draft\Data\input output
statistics 2019.xlsx',3,'C2:E31');
valoutput = xlsread('C:\Mainkan\Maritime Economics and
Logistics EUR\16. Thesis\Thesis Draft\Data\input output
statistics 2019.xlsx',3,'B3:B32');
dataval = [valinput,valoutput];
opt =
genfisOptions("SubtractiveClustering","ClusterInfluenceRan
ge",0.4,"SquashFactor",1.5,"AcceptRatio",0.5,"RejectRatio"
,0.15);
fis = genfis(trainput,traoutput,opt);
showrule(fis);
f1 = figure;
plotfis(fis);
title('FIS Rules');
epoch = 4997;
options =
anfisOptions('InitialFIS',fis,'ErrorGoal',0,'InitialStepSi
ze',0.4,'EpochNumber',epoch);
options.StepSizeIncreaseRate = 1.7;
options.StepSizeDecreaseRate = 0.9;
options.ValidationData = dataval;
[fisout,trainError,stepSize,chkFIS,chkError] =
anfis([trainput,traoutput],options);
f2 = figure;
x=(1:epoch);
plot(x,trainError,'.b',x,chkError,'*r');
title('RMSE of Training and Validation');
anfisoutput = evalfis(fisout,trainput);
anfisval = evalfis(fisout,valinput);
plotmf(fis,"input",1)
```

The Second Model Coding

```
clc
[in,out,rule] = getTunableSettings(fisout);
optune = tunefisOptions;
optune.OptimizationType = 'tuning';
optune.Method = 'ga';
optune.MethodOptions.PopulationSize = 150;
optune.MethodOptions.MaxGenerations = 1500;
optune.MethodOptions.MaxStallGenerations = 1500;
optune.MethodOptions.SelectionFcn =
{@selectiontournament,4};
optune.MethodOptions.EliteCount = 9;
optune.MethodOptions.CrossoverFraction = 0.6;
optune.MethodOptions.MutationFcn =
'mutationadaptfeasible';
optune.MethodOptions.CrossoverFcn =
{@crossoverintermediate,0.5};
optune.MethodOptions.PlotFcn = 'gaplotbestf';
[tuneanfis,info] =
tunefis(fisout,[in;out;rule],trainput,traoutput,optune);
anfisgaoutputtrai = evalfis(tuneanfis,trainput);
anfisgaoutputval = evalfis(tuneanfis,valinput);
```

The Third Model Coding

```
[in,out,rule] = getTunableSettings(fisout);
optune = tunefisOptions;
optune.OptimizationType = 'tuning';
optune.Method = 'particleswarm';
optune.MethodOptions.MaxIterations = 1500;
optune.MethodOptions.MaxStallIterations = 1500;
optune.MethodOptions.SelfAdjustmentWeight = 0.25;
optune.MethodOptions.SocialAdjustmentWeight = 0.25;
optune.MethodOptions.InertiaRange = [0.4,1];
optune.MethodOptions.SwarmSize = 150;
optune.MethodOptions.PlotFcn = 'pswplotbestf';
[tuneanfis,info] =
tunefis(fisout,[in;out;rule],trainput,traoutput,optune);
anfispsooutput = evalfis(tuneanfis,trainput);
anfispsotputval = evalfis(tuneanfis,valinput);
```