FORECASTING CONTAINER SUPPORT STRATEGY OF BANGKOK PORT

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ABSTRACT

The purpose of this thesis is to forecast the number of containers in the Bangkok Port regarding resource management, budget establishment, commercial transportation administration and management efficiency by using the non-linear auto-regressive with exogenous input (NARX) model. This model can provide an estimate and analysis of the number of containers so to determine the relationship of relevant data; for example, shipping routes, etc. A comparison of other forecasting models can be performed. The artificial neural network (ANN) and the support vector regression (SVR) are presented in this thesis. The data used regarding the number of containers was processed during the period from October 2006 to June 2014. The result shows that the mean absolute percentage error (MAPE) is approximately at 4% with 95% confidence intervals, while other forecasting models were at only 9-10%. Moreover, this model can be applied for forecasting in other sectors such as medical, industry, etc. Finally, this thesis would be most effective for forecasting the high accuracy of port logistics processing strategies.

KEY WORDS: FORECASTING / NON-LINEAR AUTO-REGRESSIVE WITH EXOGENOUS INPUT (NARX) / ARTIFICIAL NEURAL NETWORK (ANN) / SUPPORT VECTOR REGRESSION (SVR)

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FORECASTING CONTAINER SUPPORT STRATEGY OF BANGKOK PORT

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บทคัดย่อ

งานวิจัยฉบับนี้นำเสนอการพยากรณ์จำนวนตู้คอนเทนเนอร์ของท่าเรือกรุงเทพ สำหรับการบริหารจัดการทรัพยากร ตั้งงบประมาณ และการบริหารการดำเนินงานให้มีประสิทธิภาพ เพื่อกำหนดกลยุทธ์บทบาทการบริหารการจัดการรองรับการขนส่งทางการค้าได้อย่างมีประสิทธิภาพ โดยประยุกต์ใช้แบบจำลองไม่เชิงเส้นในการพยากรณ์จำนวนตู้คอนเทนเนอร์ และวิเคราะห์หาความสัมพันธ์ของข้อมูลที่เกี่ยวข้อง เช่น จำนวนสายเรือ เป็นต้น เพื่อเป็นข้อมูลป้อนเข้าให้แบบจำลองในการพยากรณ์ การสร้างแบบจำลองไม่เชิงเส้นแบบถดถอยด้วยตัวเองกับข้อมูลป้อนเข้าภายนอกไม่เชิงเส้น (Nonlinear Auto-Regressive with eXogenous input ; NARX) และเปรียบเทียบการพยากรณ์โดยใช้เทคนิคการเรียนรู้ของเครื่อง (Machine Learning) ได้แก่ วิธีโครงข่ายประสาทเทียม (Artificial Neural Network) และซัพพอร์ตเวกเตอร์รีเกรสชั่น (Support Vector Regression) โดยใช้ข้อมูลจำนวนตู้คอนเทนเนอร์ ตั้งแต่ เดือนตุลาคม พ.ศ. 2549 ถึง มิถุนายน 2557 จากนั้นทำการตรวจสอบและวัดความถูกต้องของการพยากรณ์ตามหลักสถิติ พบว่าค่าตกค้างของแบบจำลองมีความอิสระ และการแจกแจงแบบปกติที่ระดับความเชื่อมั่น 95 % พบว่าวิธีการพยากรณ์โดยแบบจำลองไม่เชิงเส้นแบบถดถอยด้วยตัวเองกับข้อมูลป้อนเข้าภายนอกไม่เชิงเส้นให้ค่าความแม่นยำดีที่สุดและค่าผิดพลาดเฉลี่ยร้อยละสัมบูรณ์เพียง 4 % ส่วนวิธีอื่น 9-10 % นอกจากนี้ยังสามารถนำแบบจำลองนี้ไปใช้ในการพยากรณ์ทางด้านอื่น เช่น การแพทย์ อุตสาหกรรม และอื่น ๆ เป็นต้น สุดท้ายงานวิจัยนี้เป็นประโยชน์อย่างยิ่งสำหรับการพยากรณ์ที่ต้องการความแม่นยำสูง

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CHAPTER I
INTRODUCTION

1.1 Rationale

International trade has been rapidly increased. Most of the worldwide trade primarily use the commercial marine transportation up to 90% of all international shipping. Therefore, the growth in container transshipment market is even more important. The port is featured as a gateway of international trade and investment.

In the future, the countries in ASEAN region will be coordinated on behalf of AEC (ASEAN Economic Community: AEC). It increasingly encourages the trade and investment within ASEAN, and other regions around the world. The availability and capacity of the port in the ASEAN region are the major factors of the key of success in AEC.

Maritime transportation is one of important parts of international trade system in the past, present and future. It is the unique feature of supporting large numbers of container and weights of cargo with lower cost than other shipments. Both inward and outward transportations of Thailand are mainly based on maritime transportation as shown in Figure 1.1. Thus, the maritime transportation is a factor influenced the ability to compete in the world markets.

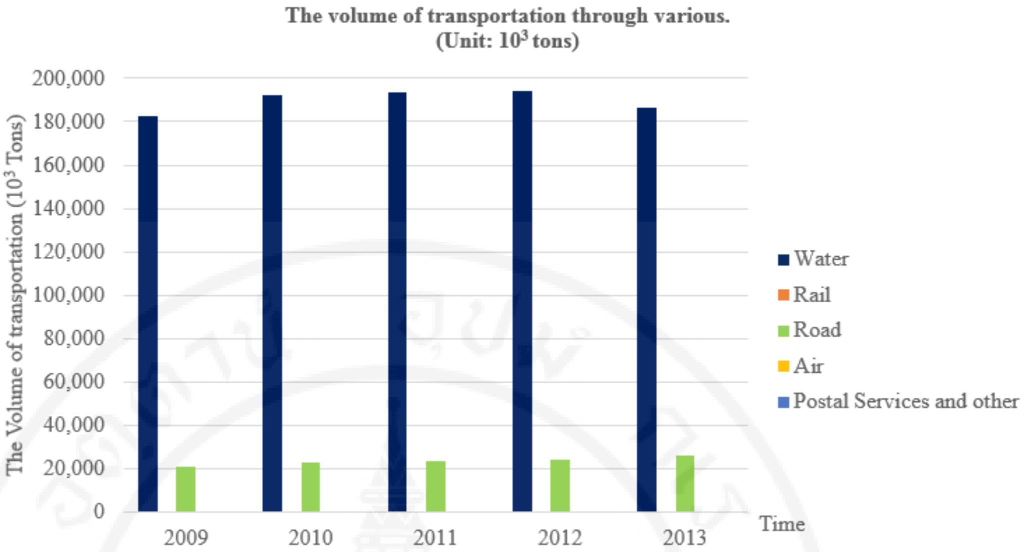


Figure 1.1 The volume of transportation through various.

Bangkok Port is the potential as the coasting port linked to other international ports. However, the port needs to be hamstrung under the government's policy by limiting the amount of transshipment container to 1.0 million TEUs. In 2004, Bangkok Port had the volume of inward and outward products. It was approximately 15.3 million tons, divided into 7.9 million tons (52%) for inward, and 7.4 million tons (48%) for outward. One of them was inward container around 0.63 million TEUs (48%), and outward containers around 0.69 million TEUs (52%), with total 1.32 million TEUs which were exceeding the government’s limitation above. Moreover, the volume of products and containers on the previous time was increasing steadily since 2009 with the average rate of 3.3% and 2.8% a year respectively [1].

In the future, Bangkok Port will plan to expand the service capacity by construction planning prof of the container depot, the truck parking yard, the yard of packing products for export, Klong Toei Square project (Trade Center), Land Physical Distribution Center, the establishment of a regional port management (Chiang Saen Port, Chiang Khong Port, and Ranong Port), and relevant logistics business. With an upgrading of container load capacity, the Bangkok Port would replace the FCL (Full Container Load) with LCL (Less than Container Load). This is because it would increase more income than the service of FCL. With 1,000 - 1,600 baht / TEU [1].

Therefore, the accurate process of forecasting container of Bangkok Port is important to administration and management on planning the organization in the future. From above, accurate forecasting is computed by the nonlinear autoregressive network with exogenous inputs (NARX). It has been accepted and widely used on the several including the peak air pollution levels forecast by using NARX models [2] and defining and applying the forecasting performance metrics on a recurrent NARX time series model [3].

This research aims to analyze forecasting the volumes of container of Bangkok Port with the nonlinear autoregressive network with exogenous inputs (NARX). The comparisons of forecasting by using Artificial Neural Network (ANN) and the Support Vector Regression (SVR) and the nonlinear autoregressive network with exogenous inputs (NARX) are given. Besides, it is used to decide the future plan for departments and organizations for improvement of the efficiency and effectiveness of the organization.

This thesis research is organized as follows: Chapter 2 reviews the relevant literature. Chapter 3 presents the research methodology. Chapter 4 presents the result and give a discussion of the result. Finally, some conclusions are provided in chapter 5.

1.2 Research Objectives

1.2.1 To forecast the container of Bangkok Port for efficient planning and decision of the departments in organization.

1.2.2 To study and analyze the comparisons of forecasting results with Artificial Neural Network (ANN), Support Vector Regression (SVR) and the nonlinear auto-regressive network with exogenous inputs (NARX).

1.3 Scope of Work

On this study, the experimental data is considered the container of Bangkok Port and the inward and outward shipping routes during the period from October 2006 to June 2014.

1.4 Expected Results

1.4.1 Proposal forecast model would help to improve the quality of service in the management of containers.

1.4.2 Forecasting would help to determine a strategy in the business plan of Bangkok Port in the next financial year effectively.

CHAPTER II
LITERATURE REVIEW

The study and research relate to forecasting container support administration and management strategy of the Bangkok Port. The forecast number of containers to assist in strategy by using the Nonlinear Auto-Regressive model with exogenous input (NARX) and the comparison of forecasting with Artificial Neural Network (ANN) and the Support Vector Regression (SVR). It starts from collecting data of containers and shipping routes during the period of the past to the present. In this chapter, the researcher studied the theory and relevant research for being the background and research methodology. These are divided into the following sections:

2.1 Container Box;

2.2 Forecasting Technique;

2.3 Artificial Neural Network (ANN);

2.4 Support Vector Regression (SVR);

2.5 Nonlinear Auto-Regressive model with exogenous input (NARX);

2.6 Accuracy Determination of Model;

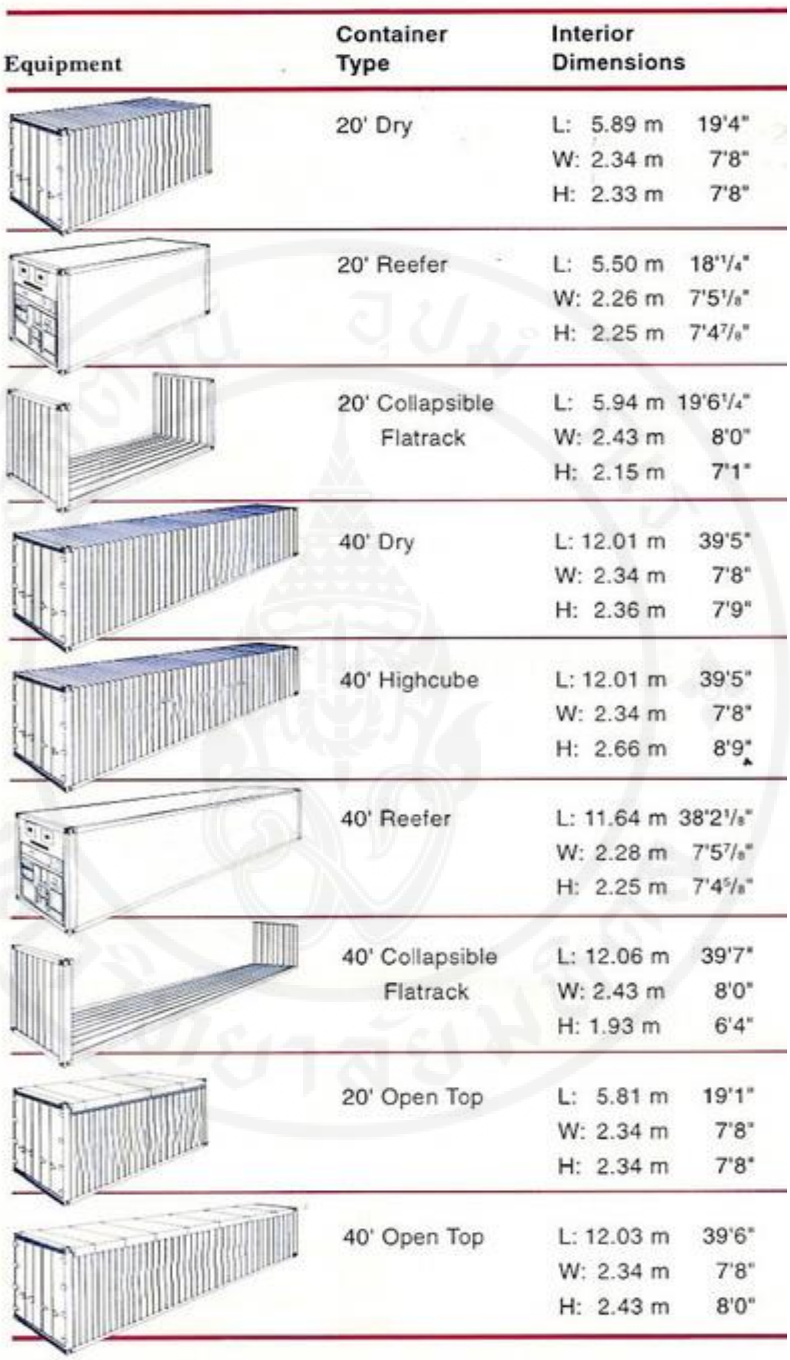
2.7 Related Research.

2.1 Container Box

Maritime transportation is considered as the most important and widely use, when it is compared to other forms of transportation, due to lower transportation costs and large number of cargo. The most of nowadays maritime transportations deal with Container Box; that is, the transported goods will have stuffing, and move the container box to be placed on the container ship, which is specially designed and used for transporting goods by container. The port will support this kind of container ship with the terminal design to be suitable to both of engineering and environment which consist of the harbor, breakwater, and other facilities [4].

The Characteristic of Container Box

The container box is the standard box made of steel or aluminum with the strong external structures. It can be stacked at least10 floors, and will be seized or slot to be the adhesion. Mostly, it has a 2-Door, which will be detailed in specifying the container number, maximum weight of product packaging, etc. When the door is enclosed, there is the locked cabinet, which will be used to hold the seal, formerly it was the lead that is different from the present which is changed to plastic. It will be coded by the number used for indicating the status. Until now, it has been developed to Electronic Seal, which can be checked via Electronic Tracking for finding the position of container movement, and within the container there is the space for placing and packing the products.



Equipment	Container Type	Interior Dimensions	
	20' Dry	L: 5.89 m W: 2.34 m H: 2.33 m	19'4" 7'8" 7'8"
	20' Reefer	L: 5.50 m W: 2.26 m H: 2.25 m	18'1/4" 7'5 1/8" 7'4 7/8"
	20' Collapsible Flatrack	L: 5.94 m W: 2.43 m H: 2.15 m	19'6 1/4" 8'0" 7'1"
	40' Dry	L: 12.01 m W: 2.34 m H: 2.36 m	39'5" 7'8" 7'9"
	40' Highcube	L: 12.01 m W: 2.34 m H: 2.66 m	39'5" 7'8" 8'9"
	40' Reefer	L: 11.64 m W: 2.28 m H: 2.25 m	38'2 1/8" 7'5 7/8" 7'4 5/8"
	40' Collapsible Flatrack	L: 12.06 m W: 2.43 m H: 1.93 m	39'7" 8'0" 6'4"
	20' Open Top	L: 5.81 m W: 2.34 m H: 2.34 m	19'1" 7'8" 7'8"
	40' Open Top	L: 12.03 m W: 2.34 m H: 2.43 m	39'6" 7'8" 8'0"

Figure 2.1 Container Type [4].

The transportation of container vessel consists of the products must be packed in container box. If the sellers pack the products by themselves; they will be called that the term CY or consignee load and count. If the shipping company packs the container box at the port or in the ICD (Inland Container Depot), which the representative of shipping company owns the location, it is also known as CFS (Container Freight Station). The products of term CY, it must be the product of FCL (Full Container Load). About Term CFS, it can be both of FCL and Consolidated; that is, the product is less than 1 unit, called LCL (Less Container Load) by Containers which are mainly used in packing have the sizes as follows:

1) 20- foot container with Outside Dimension; that is, 19.10 feet long, 8.0 feet wide, and 8.6 feet high, with maximum weight of cargo about 32- 33.5 CUM (cubic meters); including weight of cargo not exceeding 21.7 tones.

2) The cabinet with the size of 40 feet, 40 feet long, 8 feet wide, and 9.6 feet high (Hi-cute) can accept the package with 76.40- 76.88 CUM and maximum weight of cargo is 27.4 M / T, which is the weight for Dry Cargo products.

Glossary

DWT stands for Dead Weight Tonnage which is the total weight of the product, inventory and fuel tanker. It is measured in tons which depend on the ability of cargo, speed, operating period, and number of crews and passengers.

TEUs stands for twenty-foot which is a unit of packaged goods in containers sized 20 feet long. The 20-foot container is 1 TEU which means that 40-feet container equals 2 TEUs.

2.2 Techniques of Forecasting

Forecasting is the expectation or determining the volume of activity in the future to ensure that the expectation will be achieved successfully. There are many types of forecasting, and 2 types which are commonly used today consist of

1) Qualitative Forecast

2) Quantitative Forecast

The forecasting accuracy is dependent on the factors that need to be completed. If the data for forecasting is complete, it will close to the truth. For mathematical model used for forecasting the number of containers is Nonlinear Auto-Regressive model with exogenous input (NARX).

The techniques of system identification are to identify and analyze data relationships in the past time. The goal of this technique is to create a model from observation of input and output data from the system we are interested in the Mathematical Model. The system identification can be used in various fields such as the Control Systems, expectation, and forecasting [5].

This technique provides a model with many types of applications. It must start with finding out a model that is appropriate for the system we interested [5], then to create the model, and finally it is acquired to have a model checked with statistical tools to verify the accuracy of the model we provided.

2.2.1 Linear Models

The purpose of the system identification is to create a model of the system in the future regarding the function of observation data in the past. Generally, the system can be modeled as shown in Figure 2.2.

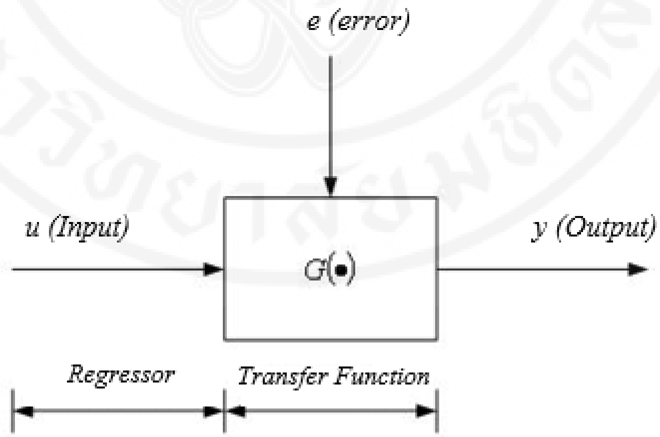


Figure 2.2 Structure of Linear Models.

Figure 2.2 shows that the main components of the model can be divided into two parts: Regressor and Transfer Function which converts the data coming from the recession as an answer or output data. Each regression models have a different function which can be shown as the equation as follows:

$$y(k) = G(q)u(k) + v(k) \tag{2.1}$$

where $y(k)$ means Output.
$u(k)$ means Input.
$G(q)$ means Transfer Function.
Q means Shift Operator.
$v(k)$ means Noise.

The Noise will be explained by using White Noise Source via the Filter as shown in Figure 2.3.

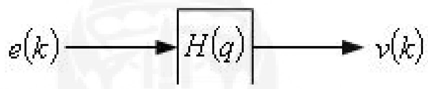


Figure 2.3 Noise $v(k)$.

From the Figure 2.2, it can be shown as the equation as follows:

$$v(k) = H(q)e(k) \tag{2.2}$$

From the equation 2.1 and 2.2, the result can be shown below:

$$y(k) = G(q)u(k) + H(q)e(k) \tag{2.3}$$

From the equation 2.2, it can be shown as the figure as follows:

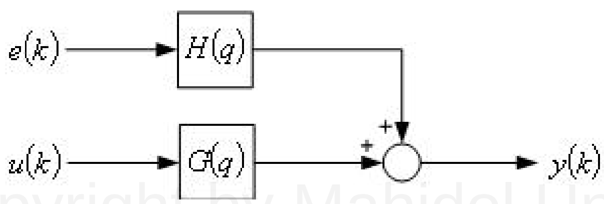


Figure 2.4 System Model.

The problem of system identification is to find a function that can make the difference between the minimal observation and forecasting values of the forecasting error. It can be written into the error of forecasting as follows;

$$e(k) = y(k) - \hat{y}(k) \quad (2.4)$$

where $e(k)$ means the Error of Forecasting
$y(k)$ means the Observation Values of Output Data
$\hat{y}(k)$ means the Forecasting Values of Output Data

From the use of various forms of models, the models can be classified into several categories which are observed by Regressor or a polynomial used in models which are commonly used.

2.2.1.1. Auto-Regressive or AR and the Regressor or *y(k - n)* lead to the model as shown in the Figure 2.5

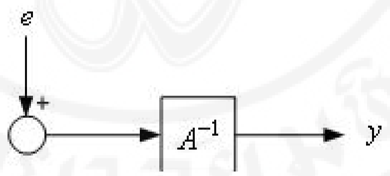


Figure 2.5 Auto-Regressive Model.

2.2.1.2. Auto-Regressive with exogenous input or ARX and the Regressor or $y(k - n)$ and $u(k - n)$ lead to the model as shown in the Figure 2.6.

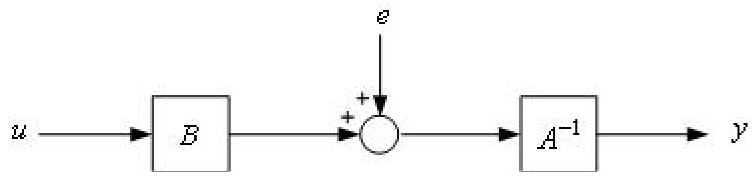


Figure 2.6 Auto-Regressive with exogenous input.

2.2.1.3. Auto-Regressive Moving Average or ARMA and the Regressor or $y(k - n)$ and $\varepsilon(k - n|\theta)$lead to the model as shown in the Figure 2.7.

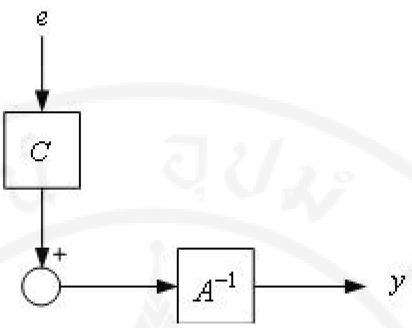


Figure 2.7 Auto-Regressive Moving Average.

2.2.1.4. Auto-Regressive Moving Average with exogenous input or ARMAX and the Regressor or $y(k - n)$, $\varepsilon(k - n|\theta)$ and $u(k - n)$ lead to the model as shown in the Figure 2.8.

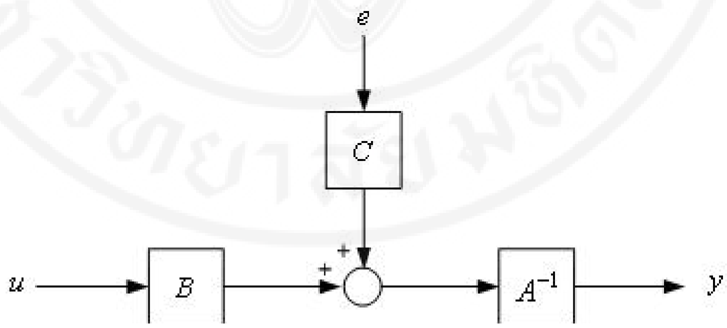


Figure 2.8 Auto-Regressive Moving Average with exogenous input.

2.2.2 Nonlinear Models

The structure of Nonlinear Models can be divided into 2 parts: Regressor and Nonlinear Function as shown in the Figure 2.9.

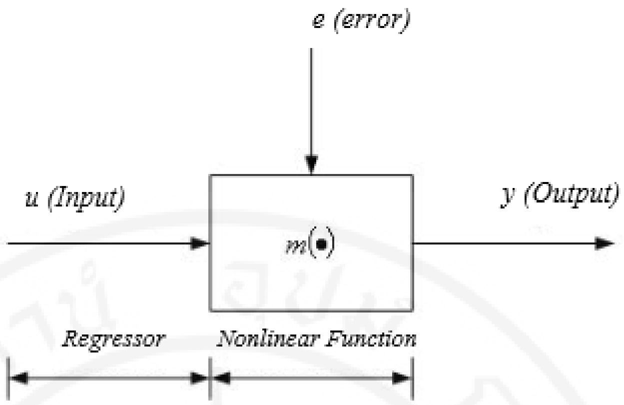


Figure 2.9 The Structure of Nonlinear Models.

Nonlinear Models can be divided likely to the Linear Models. However, there are 3 popular Nonlinear Models as follows:

2.2.2.1. Nonlinear Auto-Regressive or NAR and the Regressor or $y(k - n)$lead to the model as shown in the Figure 2.10.

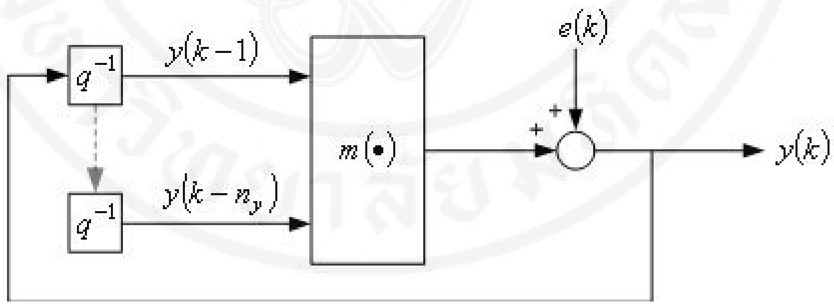


Figure 2.10 Nonlinear Auto-Regressive.

2.2.2.2. Nonlinear Auto-Regressive with exogenous input or NARX and the Regressor or $y(k - n)$ and $u(k - n)$ lead to the model as shown in the Figure 2.11.

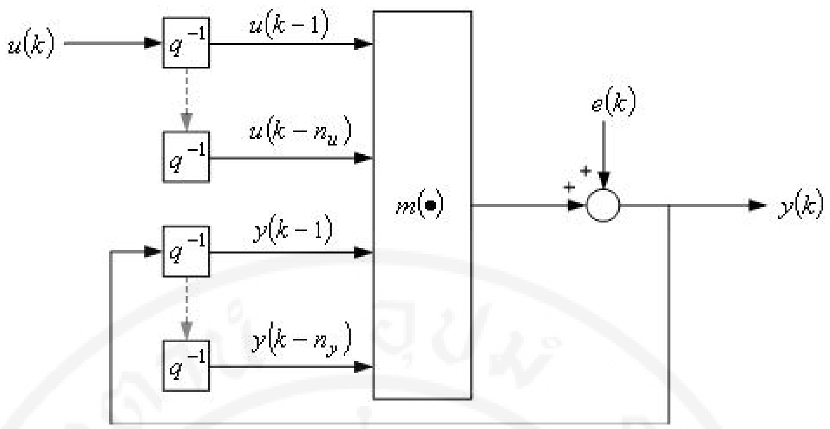


Figure 2.11 Nonlinear Auto-Regressive with exogenous input.

2.2.2.3. Nonlinear Auto-Regressive Moving Average with exogenous input or NARMAX and the Regressor or $y(k - n)$, $\varepsilon(k - n|\theta)$ and $u(k - n)$ lead to the model as shown in the Figure 2.12.

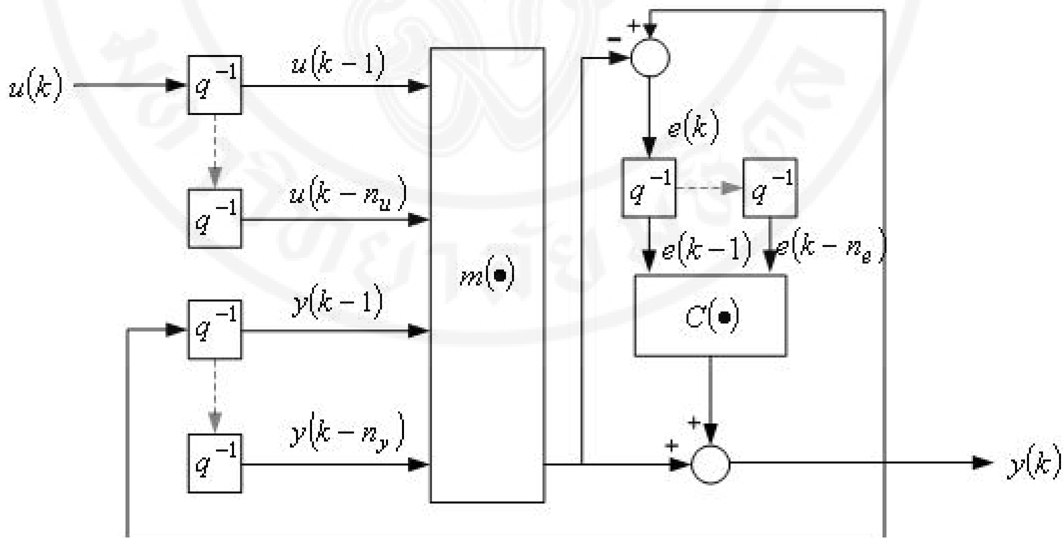


Figure 2.12 Nonlinear Auto-Regressive Moving Average with exogenous input.

2.2.3 Nonlinear Function Estimation

Function aims to be a transformer that converts multi-dimensional data to a lower dimensional input with several options such as Polynomial, Neural Network, B-Splines, and Nearest Neighbors or Interpolation etc.

2.3 Artificial Neural Network(ANN)

Artificial neural network (ANN) is mathematical information processing model and computing calculation by connectionist to simulate the performance of neural networks in the human brain in order to create a tool which has the ability to learn with pattern recognition and knowledge deduction as well as the ability in the human's brain.

The initial concept of this technique as below:

- Neurons is the bioelectric network in the brain consisting of nerve cells.
- Dendrite is synapses which each neuron is composed at the end of the nerve.
- Axon is the input and the end of neurotransmitters, which is identical to the output of the cells, these cells work on chemistry reactive power.

When they are stimulated by external stimuli or stimulated by the cells, the nerve will run through the dendrite into the nucleus, which will determine if they need to stimulate other cells to nerve or not. If the dendrite is strong enough, nuclei will stimulate other cells to go through its axon.

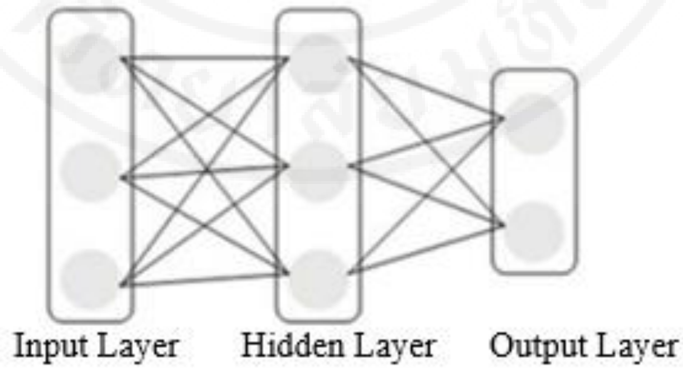


Figure 2.13 Artificial Neural Network (ANN) Models.

From Figure 2.13, it shows the characteristics of the data transmission to each Node, which will send the backward item to adjust the weights so that the results are acceptable to use in the following models; including create a network with the Node of input and Hidden node which can have many layers.

According to respecting to the Neural Network algorithm that was used in this study, the feed-forward neural network, also called Multilayer Perceptron was used. In the training of a Multilayer perceptron, back propagation learning algorithm (BP) was used to perform the supervised learning process. The feed-forward calculations which are used in this experiment, the activations set to the values of the encoded input fields in Input Neurons [6]. The activation of each neuron in a hidden or output layer is calculated as follows:

$$b_i = \sigma\,(\Sigma_j w_{ij} P_j), \tag{1}$$

where, b_i is the activation of neuron i^{th} neuron and j^{th} neuron is the set of neurons in the preceding layer; w_{ij} is the weight of the connection between i^{th} neuron and j^{th} neuron; P_j is the output of j^{th} neuron, and $\sigma(m)$ is the sigmoid or logistic transfer function, given as:

$$\sigma(m) = 1/(1+e^{-m}), \tag{2}$$

The implementation of back propagation learning updates the network weights and biases in the direction in which the system performance increases most rapidly.

2.4 Support Vector

2.4.1 Support Vector Machines: SVM

Support Vector Machine is the new model of neural network that is built to resolve the problem of traditional neural networks. The support vector machine is based on knowledge from the theory of statistical knowledge and Statistical Learning Theory and Structure Risk Minimization Principle to be used as the selection process of the appropriate form of learning model. For this reason, it will cause to get the answer with the most appropriate system support vector machine which has advantages more than other neural networks in the terms of the structure and management of the resulting data, the support vector machine and began the Yom began to be used in the field of pattern recognition, which is selected on using Support Vector. Support Vector Classification, and the function is estimated by using Support Vector Regression to deal with such problems [7].

2.4.2 Support Vector Regression: SVR

Support vector regression or SVR can be explained by the concept of using some current and historical data. The system would be trained to learn the Pattern to forecast the outcome of the upcoming future. It is believed that nature had happened in the past may happen again in the future. Therefore, Historical Space: H-Space will result in a closer or as a representative of the actual data in the Target Space: T-Space as shown in Figure 2.14.

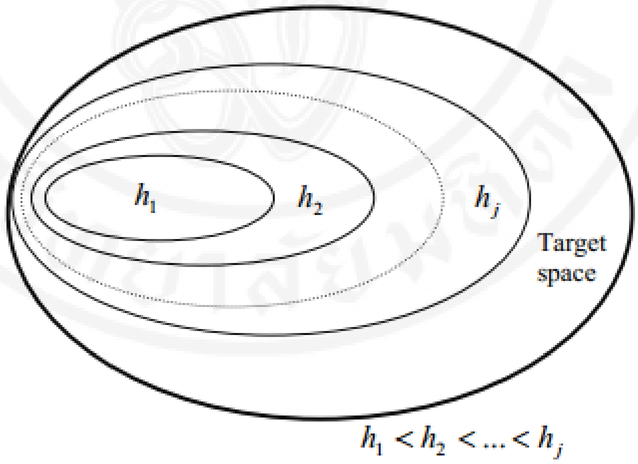


Figure 2.14 The relation of target groups in Historical Space: H-Space and Target Space: T-Space.

If the data is normally distributed, the number will represent much more data, resulting in reducing the error. However, in the case of data is affected by factors or events that occurred in the past, or changed in the temporary time which is different from the past. By calculating the basic statistics, it does not make the mistake of using data decrease. The increasing complexity of the data will lead to the increasing total of error; and easy to have the condition of Over Fitting. Thus, the more choosing the appropriate number, the more result is better which is a method of SVR.

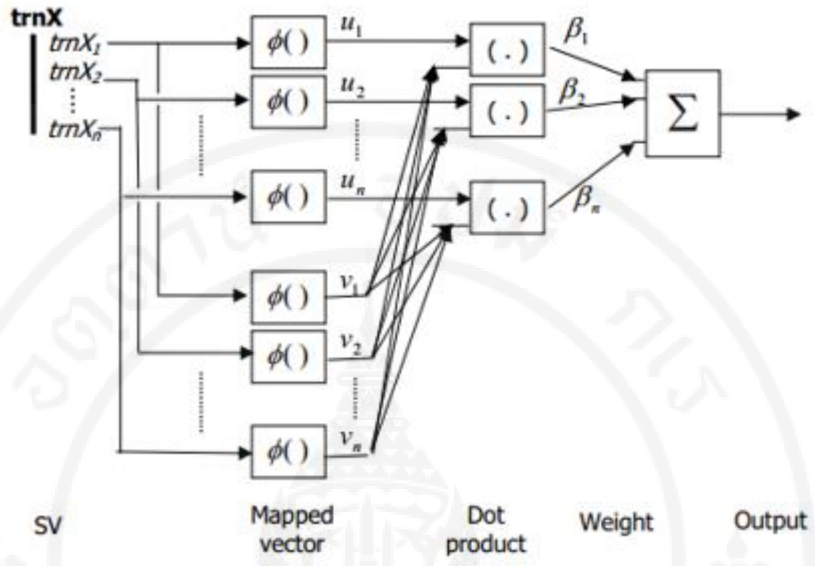


Figure 2.15 The Structure of SVR in practice mode [8].

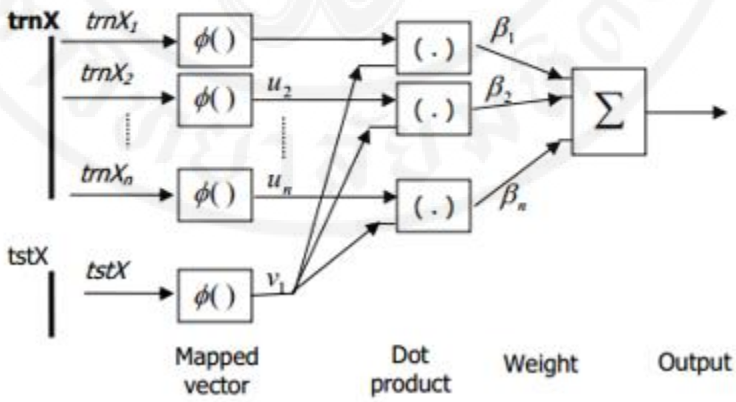


Figure 2.16 The Structure of SVR in the test and working mode [8].

From Figures 2.15 – 2.16, the structure of SVR is important in determining the apparent space which consists of Mapped Vector and Dot Product. They can be selected as appropriate for the type of used data. If they are selected as a linear function, the Output Results will be averages of learning as the linear and suitable to the nature of the relationship between Input and Output data in the linear form. On the other hands, when the function is Non- linear, the response to relation of input-Output data which are Non- linear will provide better results [7-8].

2.5 Nonlinear Auto-Regressive with exogenous input (NARX)

Dynamic neural networks are good at time series prediction. The nonlinear auto-regressive with exogenous input (NARX) to estimate the future values of time series based on the past time values of that time series and past values of a second time series. It could also be used for system identification, in which models are developed to offer dynamic systems.

The NARX model provides better forecasting than this input-output model. This is because the additional information of the previous values is used in NARX. However, some specific applications could not obtain the previous values, therefore the use of input-output model instead of the NARX model is concerned for those case [9].

NARX models, the non- linear generalization of the well-known ARX models, constitute a standard tool in linear black-box model identification [10]. These models present a wide variety of nonlinear dynamic behaviors and have been extensively used in various applications. A NARX model is formulated as a discrete time input–output recursive equation given as:

$$\begin{aligned} y(t) &= f(y(t-1),\ldots,y(t-n_y), \\ &= u(t-1),\ldots,u(t-n_u)) + \varepsilon(t), \end{aligned} \tag{1}$$

where;

$u(\cdot), y(\cdot)$ means The model input and output;

n_y, n_u means The respective maximum lags;

$\varepsilon(t)$ means A noise term.

Generally it was assumed by Gaussian and White. The optimal predictor form of this model is given as:

$$\hat{y}(t) = f(y(t-1),\ldots,y(t-n_y),u(t-1),\ldots,u(t-n_u)) \quad (2)$$

where $\hat{y}(t)$ denotes the one-step ahead forecasting of $y(t)$. Depending on how function $f(\cdot)$ is represented and parameterized, different NARX model structures; consequently, identification algorithms are derived, for the NARX architecture shown in Figure 2.17, which is one time series as input and one time series as output [10-13].

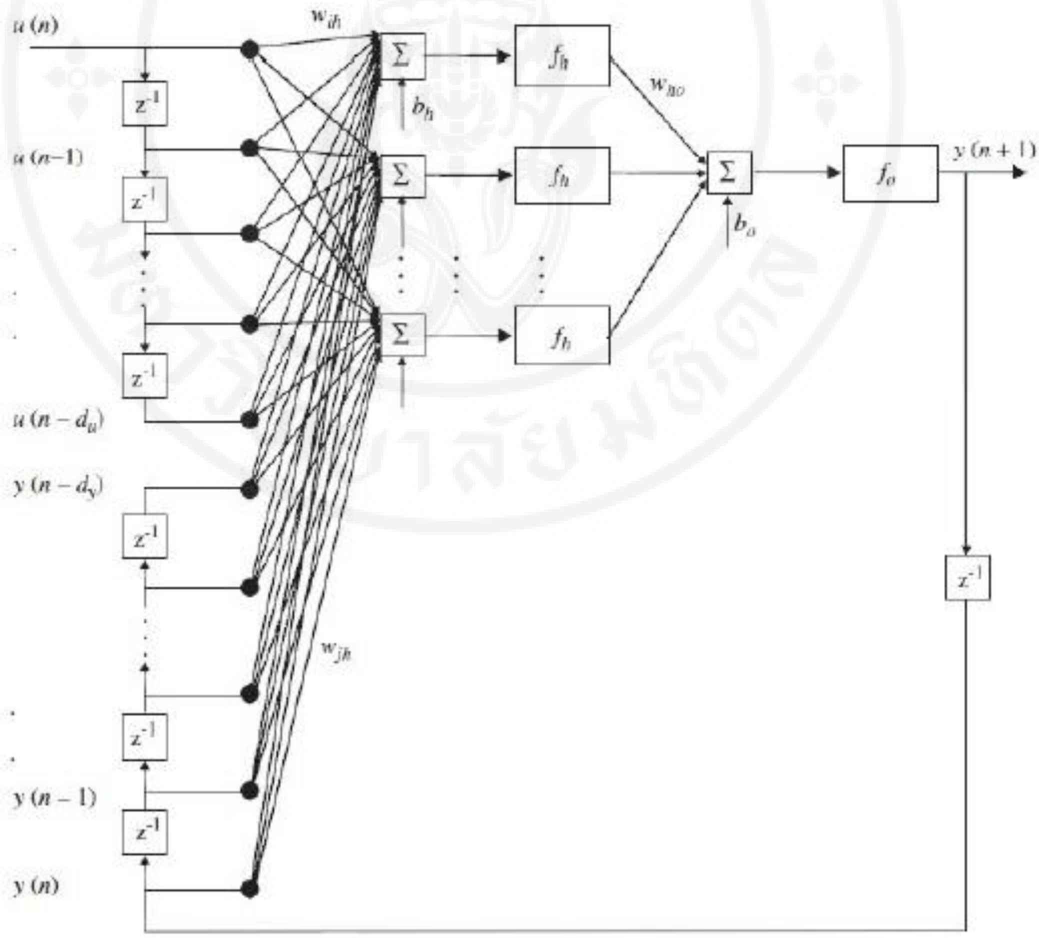


Figure 2.17 The architecture of NARX neural network [10].

The NARX can also be modeled by means of ANN. A huge literature is available on NN model theory and applications [11]. ANN are composed by simple elements connection (or neurons) operating in parallel. Each neuron's output is obtained by filtering a weighted sum of its inputs through a usually nonlinear function, the activation function. The weights associated with the network connections are tuned during the training (learning) phase in order to reduce a given cost function, including a modified cost function (or MSE). The ANN structure used in this study is a standard feed-forward neural network. This kind of network computes a vector function, $f_{NN} : R^Q \rightarrow R^L$.Where Q and L are the dimensions of the input and output vectors of the net, respectively, the l^{th} element of the vector function f_{NN} for the n^{th} pattern ($v^n \in R^Q$) is defined as (M is the number of the neurons in the hidden layer) [10-13].

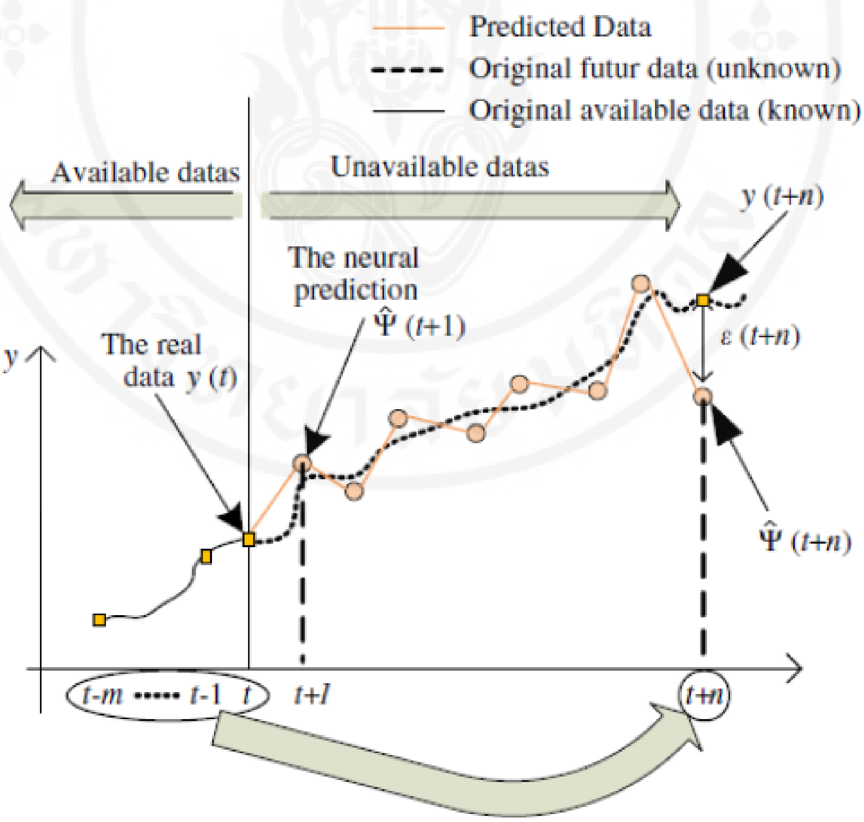


Figure 2.18 Residual error obtained at each prediction [11].

2.6 Model Validation

The validation of forecasting method in accordance with the criteria, it must be needed to know whether the forecasting model to be utilized in the decision is accurate and reliable or not. For qualitative forecasting, it is going to be difficult to determine. However, for quantitative forecasting, it can use the models for testing with three conditions as follows:

1) Independence of Residuals Validation
2) Normal Distribution of Residuals Validation
3) Correlation between Residuals and Input Validation

Residuals can be used in several of the statistical tests, such as Autocorrelation Test, Cross correlation Test, and Normality Test.

2.6.1 Autocorrelation Test

Autocorrelation Test is the independence measurement of the time series at some times on another time to see if they are related or not [14].

2.6.2 Cross correlation Test

Cross correlation test is the measure of the two sets of time series that are related or not by considering to N which is the pair of observations on the time series x_t and y_t[14].

2.6.3 Normality Test

Normality Test is the test of residuals to see if it is distributed according to a normal distribution or not. If the residuals do not follow the normal distribution, it means that the model has the error which is based on the assumption created in the beginning [14].

2.7 Related Research

Thouverez, et al. [15] found that a linear estimation of structure had the error, if it had the non-linear problems. This will affect on the dynamic response.

Hence, it has been used by NARX model interoperability to reduce the number of parameters that must be identified and possible which led to a multi-dimensional mechanics, and the models are also made of minimize non-linear parameters.

Huang, et al. [16] proposed a new forecasting method, in order to alleviate the limitation of traditional statistical models utilizing only structured data, which is able to take full advantage of domain knowledge and avoid many kinds of biases and inconsistencies inherent in subjective judgments. The new method is applied to forecasting the container throughput of Guangzhou Port, one of the most important ports of China. In order to test the effectiveness of the new method, we compare its performance with that of the frequently-used ARIMAX model. The results show that the new method significantly outperforms the ARIMAX model.

Zemouri, et al. [3] proposed the NARMAX models with the proposition of a scheme for providing the time series forecasting successfully demonstrated for modeling the input–output behavior of many complex systems. The approach is based on a recurrent NARX model, obtained by linear combination of a recurrent neural network (RNN) output and the actual data output. Some forecasting metrics were used to assess the quality of predictions. The metrics were enabled to compare the different prediction schemes, providing an objective way to measure the changes in training or prediction model (ANN), affecting the quality of predictions. The results of proposed NARX approach consistently outperformed the forecasting obtained by the RNN.

Pisoni, et al. [2] presented Air pollution has a negative impact on human health. For this reason, it was important to correctly forecast over-threshold events to give timely warnings to the population. Nonlinear models of the nonlinear auto regressive with exogenous variable (NARX) class had been extensively used to forecast air pollution time series, mainly using artificial neural networks (NNs) to model the nonlinearities. This work discusses the possible advantages of using polynomial NARX instead, in combination with suitable model structure selection methods. Furthermore, a suitably weighted mean square error (MSE) (one-step-ahead prediction) cost function is used in the identification/learning process to enhance the model performance in peak estimation, which was the final purpose of this application. The proposed approach was applied to ground-level ozone concentration time series. An extended simulation analysis was provided to compare the two models on a selected case study and to investigate the effect of different weighting functions in the identification performance index. The results shown that polynomial NARX were able to correctly reconstruct ozone concentrations, with performances similar to NN-based NARX models, but providing additional information, as, e.g., the best set of regressors to describe the studied phenomena. The simulation analysis also demonstrated the potential benefits of using the weighted cost function, especially in increasing the reliability in peak estimation.

CHAPTER III
RESEARCH METHODOLOGY

From the theory and related research, the problem in this research is the nonlinear problem. Therefore, the researcher chose to use nonlinear models for forecasting the containers. The nonlinear model can solve the problem of multiple input and simple output very well; including in the case of the nonlinear problem. Finally, the researcher chose nonlinear auto-regressive model with exogenous input (NARX) and comparison of forecasting by using the techniques of machine learning consisted of artificial neural network (ANN) and the support vector regression (SVR) to forecast the containers. The research methodology consists of:

3.1 Diagram of research methodology;

3.2 The quantity of container (TEU);

3.3 Forecasting of containers by using Machine Learning;

3.4 Determining the accuracy of the model.

3.1 Diagram of research methodology

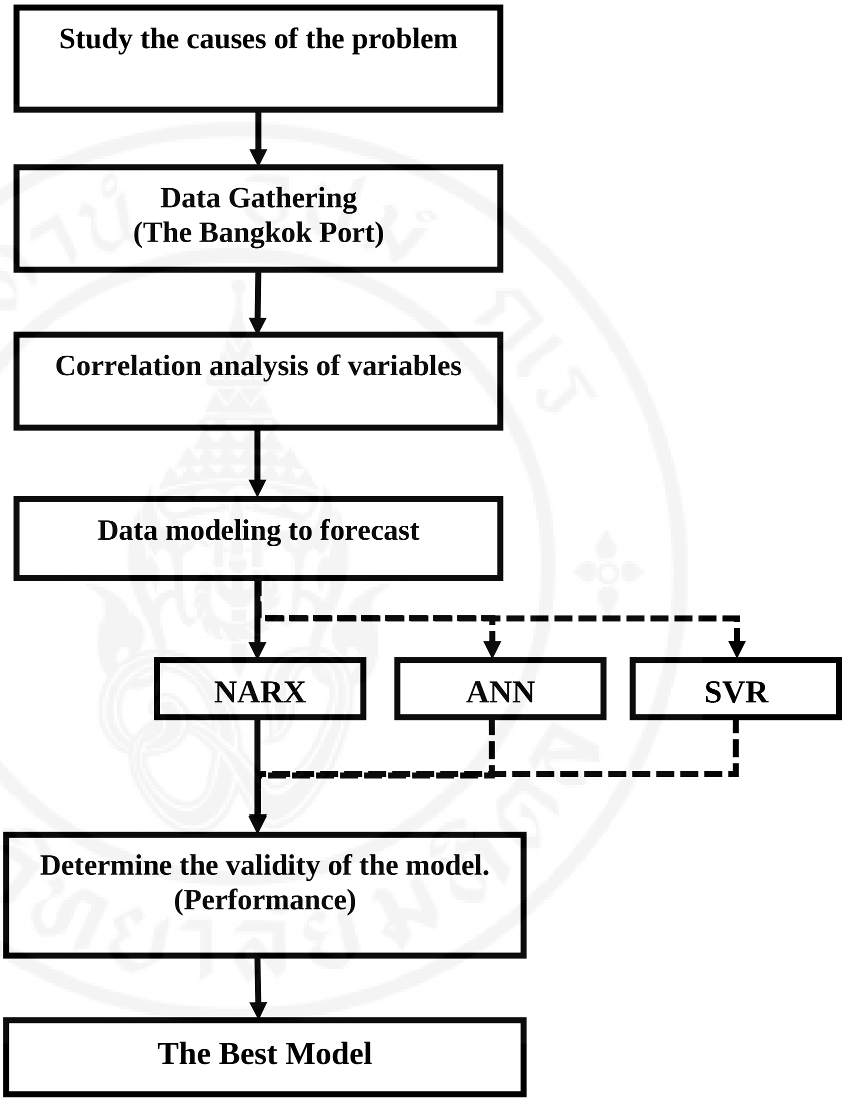


Figure 3.1 Diagram of research methodology.

3.2 The Quantity of Container (TEU)

The data used in this study was a secondary data which once had already collected, consisted of the volume of container and inward and outward vessels of Bangkok Port during the period from 2006 to 2014 as shown in Figure 3.2 and 3.3.

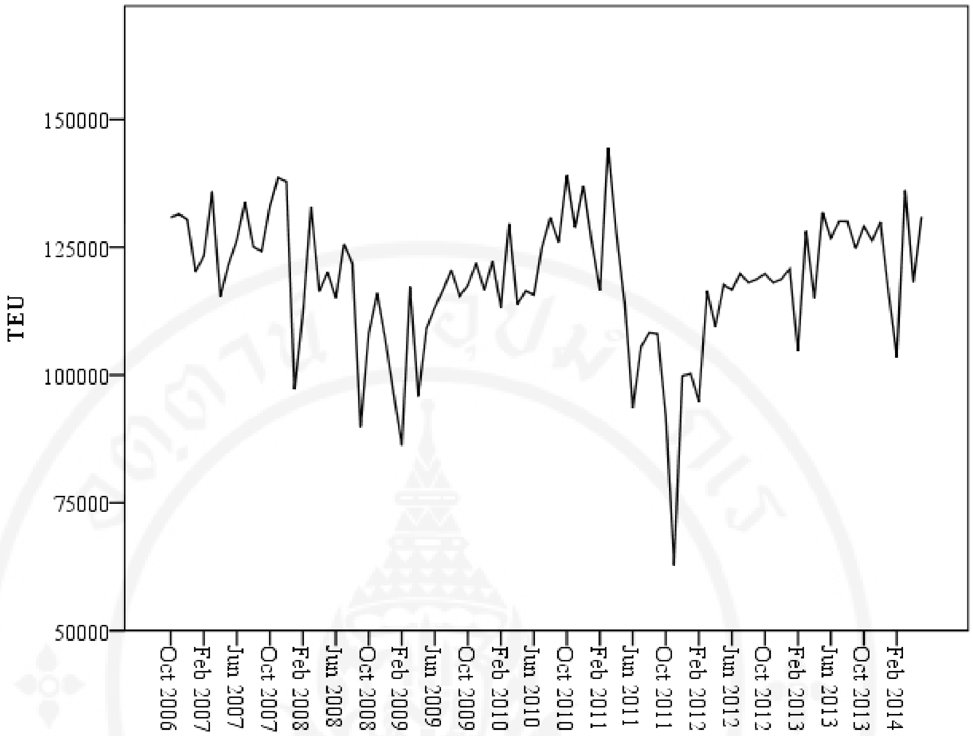


Figure 3.2 The quantity of container (TEU).

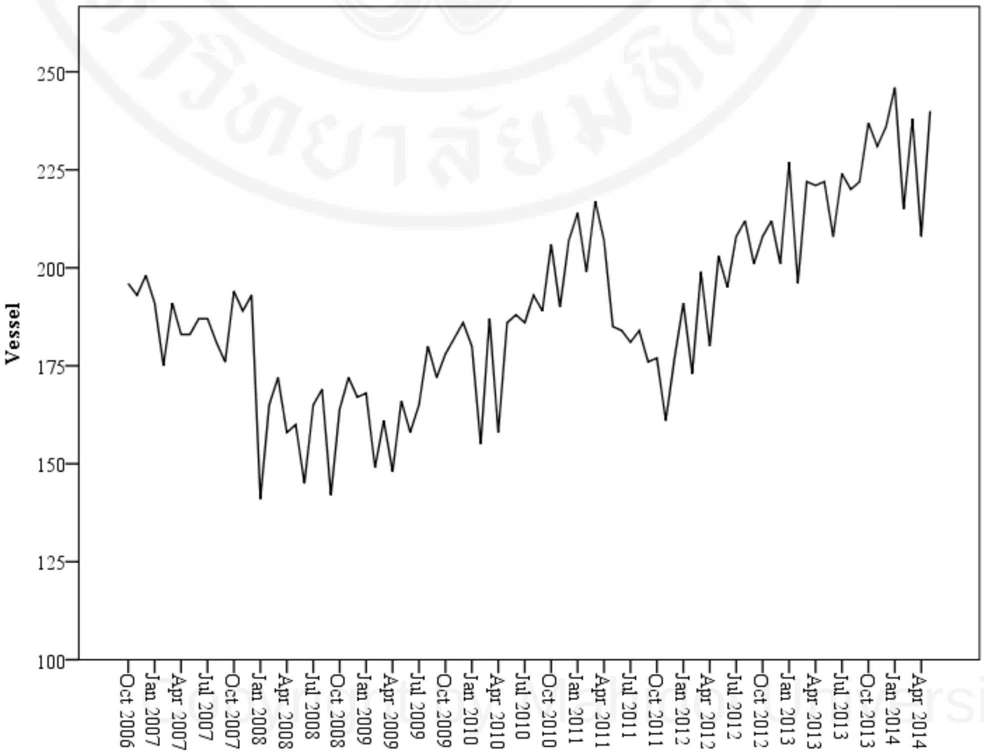


Figure 3.3 The quantity of vessel.

3.3 Forecasting of containers by using Machine Learning

The prepared time series data consisted of the container and vessels which were the monthly data to create a model to forecasting as the details below.

3.3.1 Artificial neural network; ANN

This would be used by the program of Weka 3.7.12 for creating the models in forecasting as the following setting:

Debug : False

Num Fuction : 3

Num Threads : 1

Pool Size : 1

Ridge : 0.01

Seed : 3

Tolerance : 1.0 x 10^{-6}

Use CGD : False

3.3.2 Support Vector Regression: SVR

This would be used by the program of Weka 3.7.12 for creating the models in forecasting as the following setting:

SVM Type : epsilon-SVR (regression)

Cache Size : 100

Coef0 : 0.0

Cost : 100

Debug : False

Degree : 100

Do Not Replace Missing Values : False

Eps : 0.001

Gamma : 0.0

Kernal Type : liner : u’ x v

Loss : 0.1

Mode File :Weka-3-7

Normalize : True

Nu : 0.5

Probability Estimates : False

Seed : 1

Shrinking : True

Weight :

3.3.3 Nonlinear Auto-Regressive model with exogenous input (NARX)

3.3.3.1 Determining the input data of models

The model used for solving the problem was Nonlinear Auto-Regressive with exogenous input (NARX) which had the regressor as follows: $y(k-1),\ldots,y(k-n_y),u_j(k-1),\ldots,u_j(k-n_{uj})$as shown in Figure 3.4.

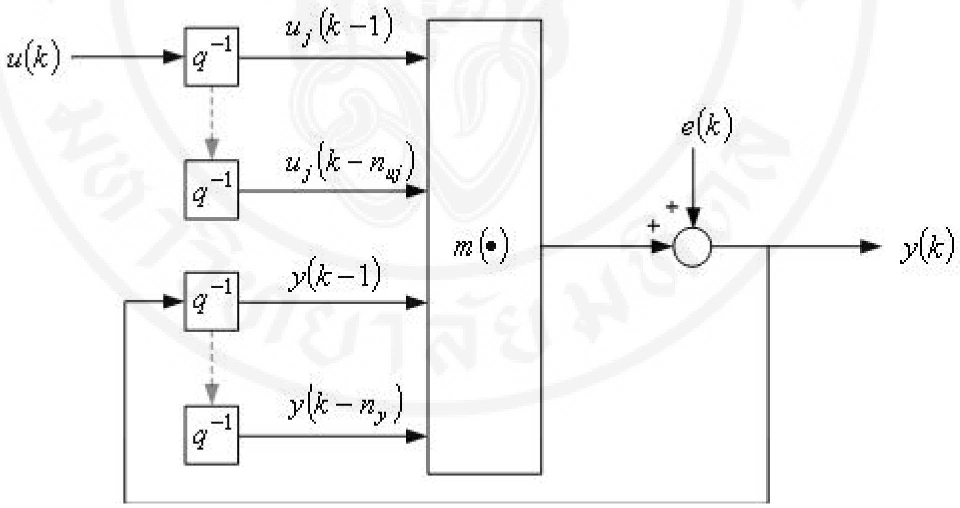


Figure 3.4 Nonlinear Auto-Regressive model with exogenous input (NARX).

The NARX network uses the past values of the actual time series to be predicted and past values of other inputs (like currencies of other nations and technical indicators in our case) to make predictions about the future value of the target series. These networks are again classified as series and parallel architecture [17].

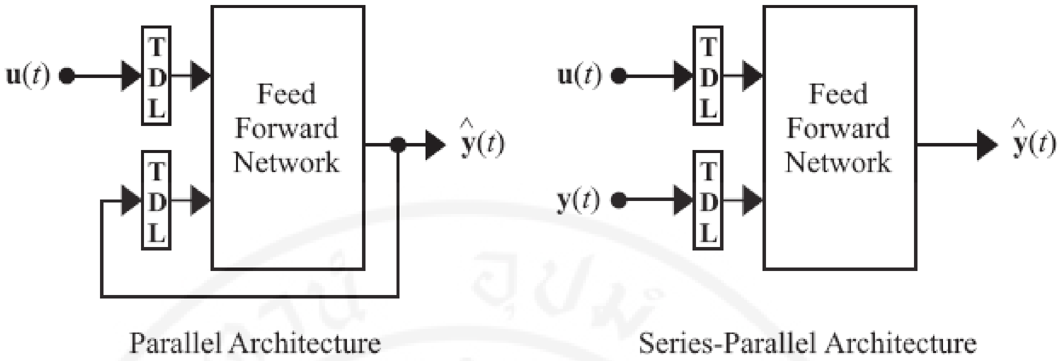


Figure 3.5 Parallel and series parallel architectures of NARX networks [17].

In Figure 3.5, *u*(*t*) represents the past exogenous values (currencies of other nations and technical indicators in our case) *y*(*t*) represents the past values of the actual series to be predicted. (*t*) indicates the predicted values. If past values of actual series are not being recorded, they will not be available to the system. In such situations the networks uses its past predicted values. In our case we will have the actual past values; hence we prefer to use them instead of our predictions. Thus we are able to base the model on actual values which are more reliable than our predictions.

3.3.3.2 Selection of neural network type [18]

Neural networks can in general be divided into two categories – static anddynamic. Static networks have no feedback elements and no delays. The output is calculated directly from the current inputs. Such networks assume that the data is concurrent and no sense of time can be encoded. These networks can thus lead to instantaneous behavior.

Dynamic networks may be difficult to train but are more powerful than static networks. As they have memory in form of delays or recurrent loops, they can be trained to learn sequential or time varying patterns. This makes them networks of choice for various applications like financial predictions, channel equalization, sorting, speech recognition, fault detection etc.

Since we are dealing with a time series it is necessary to use dynamic networks. Dynamic networks can be of two types ones with feed forward connections and taps and those with feedback or recurrent networks.

At this stage two breeds of networks were considered the NARX (Nonlinear Autoregressive Neural Network) and recurrent networks. NARX networks use taps to set up delays across the inputs and also incorporates the past values of the output. Recurrent networks have loops within intermediate layers and incorporate memory via these loops.

Both the networks have been employed in dynamic applications .The difficulties and the time required in training the recurrent networks is a known problem. To evaluate the resources requires by each of these networks, a batch of 40 Networks (1 neuron to 40 neurons) was trained under the same conditions for same datasets and training parameters (MATLAB® Neural Network Toolbox).

The basic NARX network is used for multistep predictions. It is assumed that actual past values of target are not available and the predictions themselves are fed back to the network. Since we will have access to the actual past values we will provide those values instead of our past predictions. This helps the system train on actual values rather than predictions.

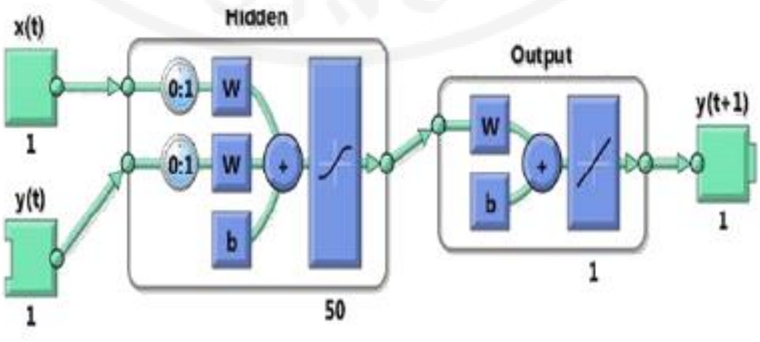


Figure 3.6 Network diagram.

Fitness Assignment in this experiment was Mean Square Error or MSE which could be calculated by

$$MSE = \sum_{i=1}^{N} \frac{(y_i(t) - \hat{y}_i(t))^2}{N} \tag{3.1}$$

When, (t) means the container of that day, $\hat{y}_i(t)$ means the container of forecasting and N means the numbers of data.

3.3.3.3 Experimental Methodology

In this experiment, there were 94 data which were represented 100 percent of the data, and set to be used for finding 70 percent (66 data) of coefficient and 15 percent (14 data) of other information to test the validity of the model that is accurate to the data or not. About 15 percent (14 data) of remaining data, it will be used for forecasting and determining on the accuracy to the information which had not been seen.

3.3.3.4 Function approximation

Here we will assume that we can feed the returns series value at each instance and we can then try to predict the return value at each day. We just map the targets within the neuron range and train the network using an algorithm that is suited for such an application. The MATLAB® Neural Network Toolbox [17] provides a detailed survey of algorithms appropriate for various applications. The results therein state that Leven berg-Marquardt (LM) is a good algorithm for small function approximation problems. Scaled conjugate gradient algorithm (SCG) shows good performance for problems of all sizes, and is especially good for large networks. Hence we decide to use scaled conjugate gradient algorithm for training in this approach.

We will train the NARX network over all scaled values and SCG algorithm. If the value of this predicted signal is positive and above a threshold, we anticipate a positive return and buy, if it is negative and below a threshold we short. Else we stay out of the market. These thresholds are set to remove some small values from the decision making process as they are deemed to be unreliable. [17-18]

3.3.3.5 Network architectures to be considered

The NARX networks will have a linear input layer of neurons (default by MATLAB®) for the hidden and the output layers we will use the Tansig neurons. Tansig neurons and sigmoid neurons have been extensively used in most of the neural network applications. Both of them are similar in behavior and have a similar looking transfer function except for the range of outputs that they can generate. A sigmoid layer has a range from 0 to 1 whereas the range for Tansig transfer function ranges from -1 to 1. Klimasauskas [19] suggests that sigmoid neurons be preferred to determine average behavior and Tan based layers to find deviations from normal. The application at hand also prompts us to use the Tansig layer. Additionally our development environment the MATLAB® Neural Network Toolbox also recommends Tansig layers for pattern recognition problems and provides it as the default layer. [17-19]

3.3.3.6 Number of layers

We have a linear layer of linear neurons at the input; the number of neurons in this layer will be equal to the number of inputs that we have provided to the networks. Using linear neurons at the input is a standard practice and is used merely as an interface between the inputs and the hidden layers. In fact MATLAB® Neural Network Toolbox does not count it as an independent layer. There is no certain figure for the number of hidden layers to be used. Cybenko [20] Hornik, et al. [21] show how a single layer of hidden neurons is capable of adapting to complex functions. Survey papers on this field [22] also reveal how a single hidden layer of neurons is the most preferred option. Using additional layers adds up complexities to the model and increases the time required for training and simulation.

The framework described earlier has capabilities to generate, simulate networks with multiple hidden layers. It can be seen from the code that the framework can generate the number of layers specified by the user, and use user specified number of layers for each layer. However the limited processing resources available did not permit us to perform tests with several layers, hence we too decided to use single layer of hidden neurons for this research. The inputs were mapped in the input range of -1 to 1 by our massager. The outputs were also to be mapped within this range. Naturally Tansig was the output neuron of choice since it maps the inputs to this range. A single output neuron was thus used at the output.

3.3.3.7 Number of Taps and Hidden Neurons:

The tapped delay line of the NARX network allows passing of past values to the network. They make the data sequential unlike the original concurrent dataset. Thus these taps set up a sense of time and correlation of past values. The numbers of neurons are supposed to be related to the complexity of the application at hand as each neuron in the hidden layer contributes weights and flexibility to the network. There is no standard method to determine the number of neurons to be used and several thumb rules are used. Mehta [23] has stated how the architecture depends on these thumb rules and it is not necessary that they work well.

3.4 Determining the accuracy of the model

When the model was created, it needed to be determined the accuracy of the model which had 3 conditions on testing as follows:

1) Independence of Residuals

2) Normal Distribution of Residuals

3) Correlation between Residuals and Input

Then, to compare 3 conditions for finding the accuracy of modelby using the methods as follows:

1) Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(y_i(t) - \hat{y}_i(t))^2}{N}} \tag{3.2}$$

2) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{((y_i(t) - \hat{y}_i(t))}{(y_i(t)}\right| x\ 100 \tag{3.3}$$

3.5 Research Conclusion

Regarding above methodology, when we set the input to the model, and forecasting model configuration of input and nonlinear output, then be conducted by the nonlinear autoregressive network with exogenous inputs (NARX) and compared the forecasting by using artificial neural networks (ANN) and support vector regression function (SVR). From this, it led to the nonlinear model for demonstrating the system; in order to be used in forecasting the container. The findings of this research will be presented in Chapter 4.

CHAPTER IV

EXPERIMENT AND RESULTS

From the research methodology in Chapter 4, firstly the researchers collected 94 data of container during the period from October 2006 to June 2014 as shown in Figure 4.1. Next, nonlinear auto-regressive with exogenous input (NARX) model was created. Then, it needed to analyze the input data to the model; and compare on forecasting by using artificial neural network (ANN) and support vector regression (SVR). Finally, the model had to be checked the accuracy of the model; including chosen the best way to forecasting in the future. There are the results from this experiment as follows:

4.1 The tools used in the experiment;

4.2 The analysis of the data and the comparison on the accuracy of models in forecasting;

4.3 The results from verifying the validity of the model;

4.4 The conclusion of research.

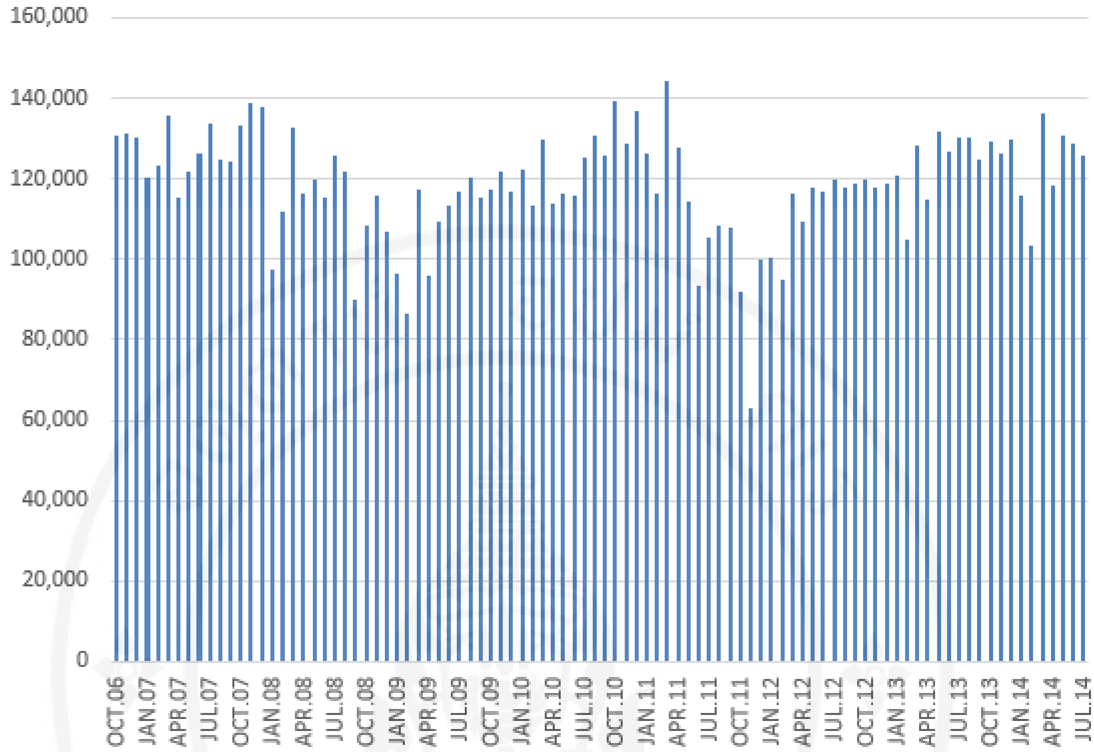


Figure 4.1 The quantity of container (TEU).

4.1 The tools used in the experiment

From this research, there are the tools used in the experiment as follows:

- IBM SPSS Statistics 21
- Weka 3.7.12
- MATHLAB R2014b
- Microsoft Office Excel 2010

4.2 Data analysis

According to data distributions, Autocorrelation Test, and Crosscorrelation Test, the test results have shown in the Figures 4.2 - 4.4.

One-Sample Kolmogorov-Smirnov Test

		TEU	Vessel
N		94	94
Normal Parameters[a,b]	Mean	118514.20	190.26
	Std. Deviation	13346.181	24.245
Most Extreme Differences	Absolute	.131	.062
	Positive	.053	.062
	Negative	-.131	-.039
Kolmogorov-Smirnov Z		1.271	.603
Asymp. Sig. (2-tailed)		.079	.860

a. Test distribution is Normal.

b. Calculated from data.

Figure 4.2 P-value of normal distribution of container and vessels.

From Figure 4.2, it can be described as a p-value is greater than 0.05. The container and vessels have a normal distribution with 95% confidence intervals.

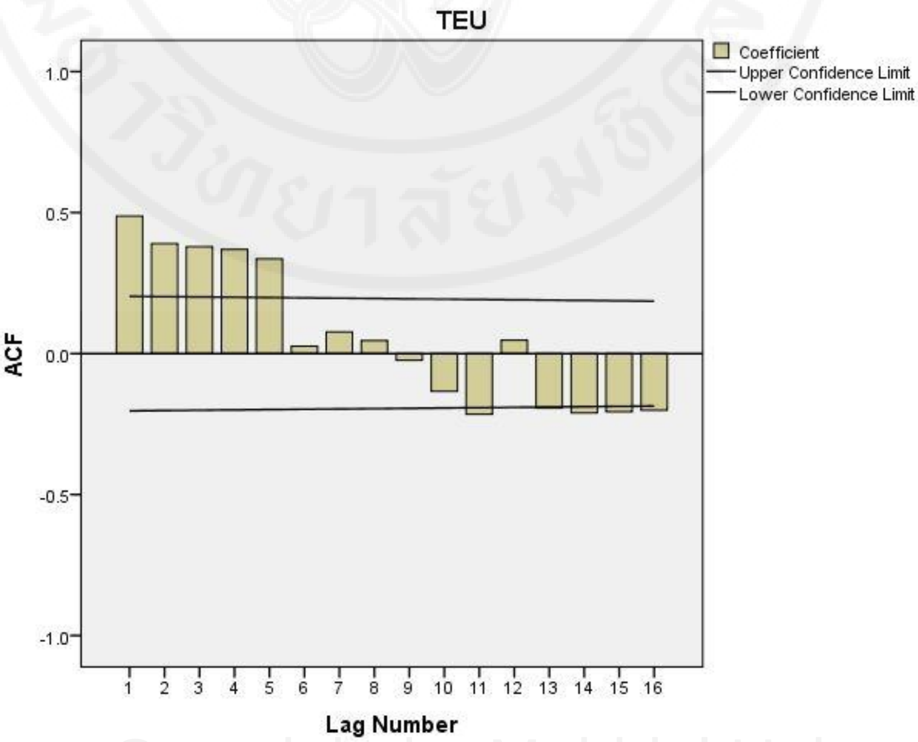


Figure 4.3 Autocorrelation Test of Container.

From Figure 4.3, it can be described by the number of retroactive container from the 1st month to the 4th month to the present container.

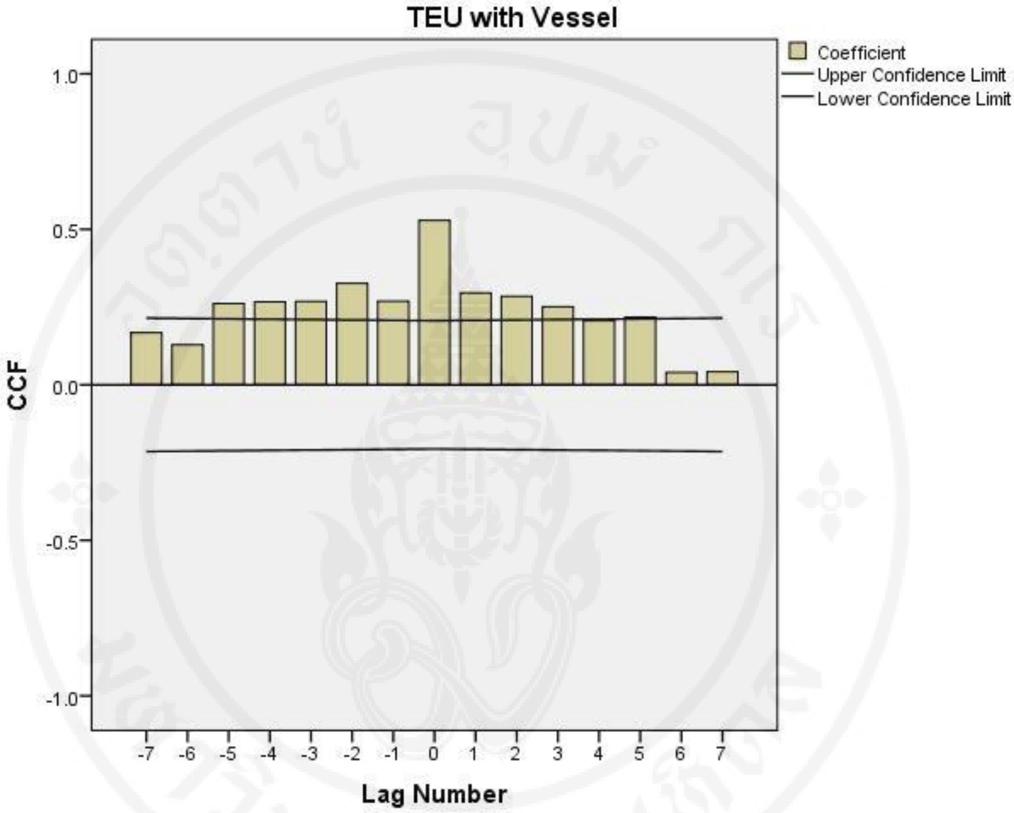


Figure 4.4 Correlations Test between container and vessels.

From Figure 4.4, it can be described by the vessels affecting on the retroactive container from the 1st month to the 4th month.

From Figures 4.3 - 4.4, it is found that all the correlations are outside to the confidence interval which allows us to select the input of the model as follows:

1) The number of vessels (u)

2) Container (y)

Table 4.1 The comparison of forecasting container and actual container (3 methods)

MONTH	Actual	ANN	SVR	NARX
….				
Jan-07	120199	114773.2111	113796.8874	124076.5863
Feb-07	123279	115022.8254	113796.8874	125409.6219
Mar-07	135904	138654.4944	123001.3000	137685.8077
Apr-07	115333	116046.8909	113796.8874	117967.9198
May-07	121715	114864.4048	113796.8874	118706.8697
…..				
Jun-14	128828	130080.5461	116533.0730	128099.5491
Jul-14	125827	124268.6567	113881.2205	128782.7251
Aug-14*		124096.8772	113796.8874	128401.0689

From Table 4.1, it shows the result comparison of forecasting container from 3 methods (all data can be read on the appendix); including one of forecasting result in advance by ANN is 124096.8772, SVR is 113796.8874, and NARX is 128401.0689, which are shown as a graph in Figures 4.5.-4.7.

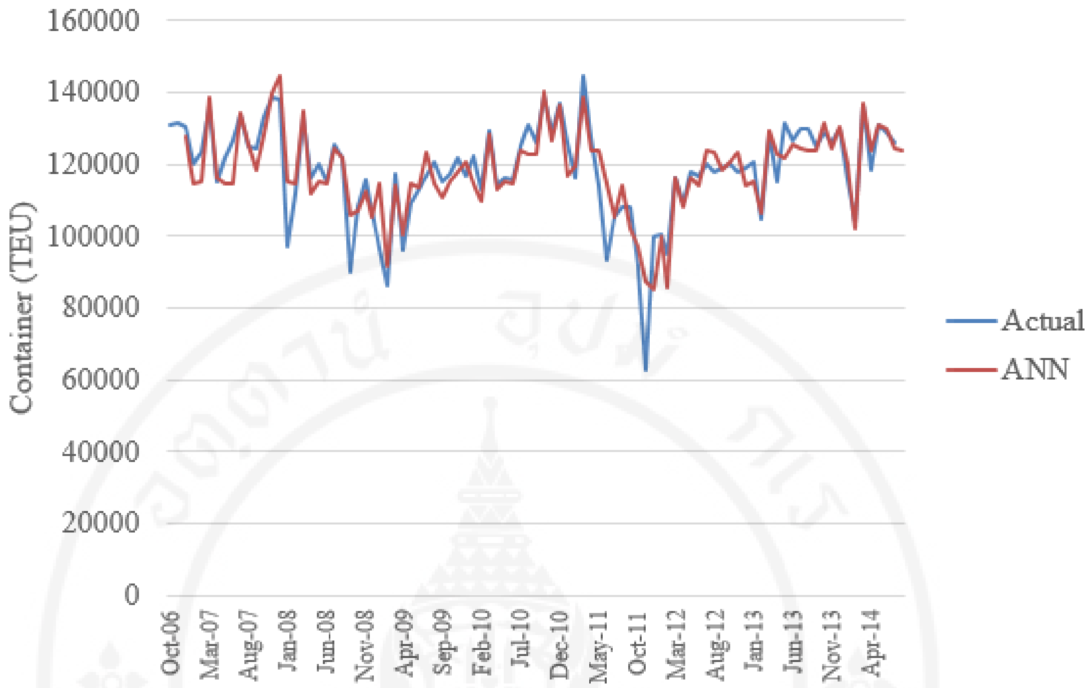


Figure 4.5 The comparison of actual value and the method of ANN.

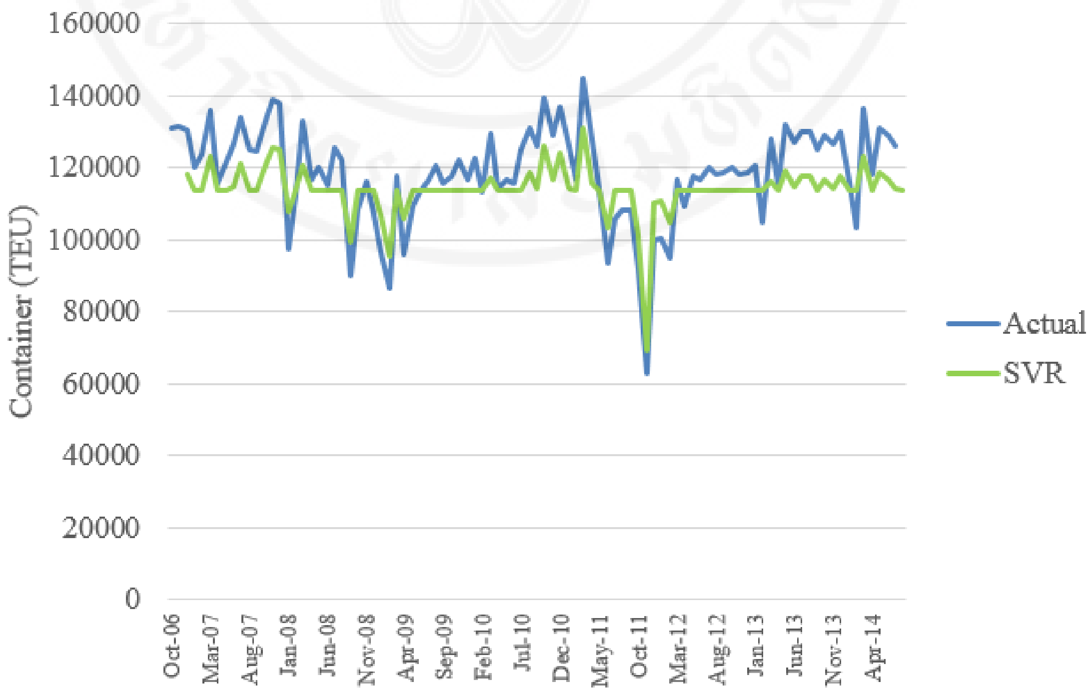


Figure 4.6 The comparison of actual value and the method of SVR.

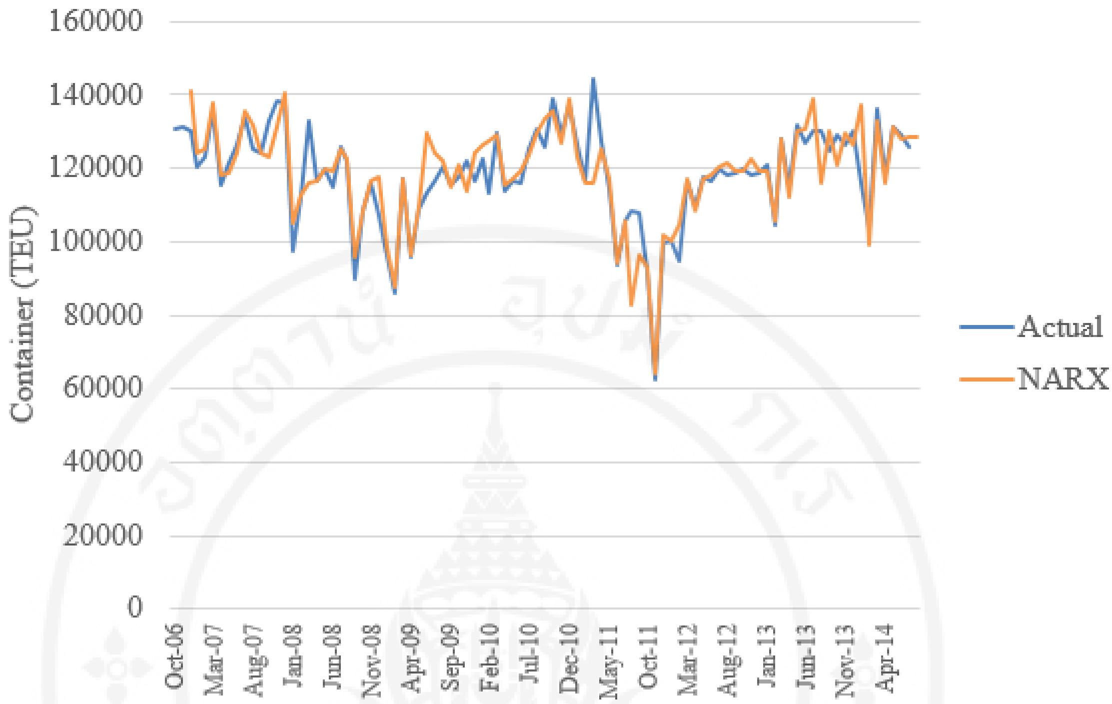


Figure 4.7 The comparison of actual value and the method of NARX.

From Figures 4.5-4.7, the results are shown the graph of actual value and forecasting value with 3 methods. It is clearly that the forecast model based on NARX is close to actual value with highest accuracy comparing with ANN and SRV as shown in Table 4.2.

Table 4.2 The comparison of accuracy value with 3 method

Performance / Model	MSE (TEU^2)	RMSE (TEU)	MAPE (%)
NARX	**4.7×10^7**	**6.8×10^3**	**3.5**
ANN	6.2×10^7	7.9×10^3	4.20
SVR	8.1×10^7	9.0×10^3	6.7

From Table 4.2, the result from determining the accuracy of monthly forecasting container, which can be ordered to the highest accuracy as follows: NARX, ANN and SRV respectively. The results consist of 1) MSE value is 4.7 x 10^7 TEU^2, 6.2 x 10^7 TEU^2, and 8.1x 10^7 TEU^2, respectively, 2) RMSE value is 6.8 x 10^3 TEU, 7.9 x 10^3 TEU and 9.0 x 10^3 TEU, respectively, and 3) MAPE value is the percentage of 3.5, 4.20 and 6.7, respectively.

4.3 The results from verifying the validity of the model

From the created model, it can be determined to the correctness of model as follows:

1) Independence of Residuals

Determining to the correctness of model by observing the Independence of Residuals is shown in Figure 4.8.

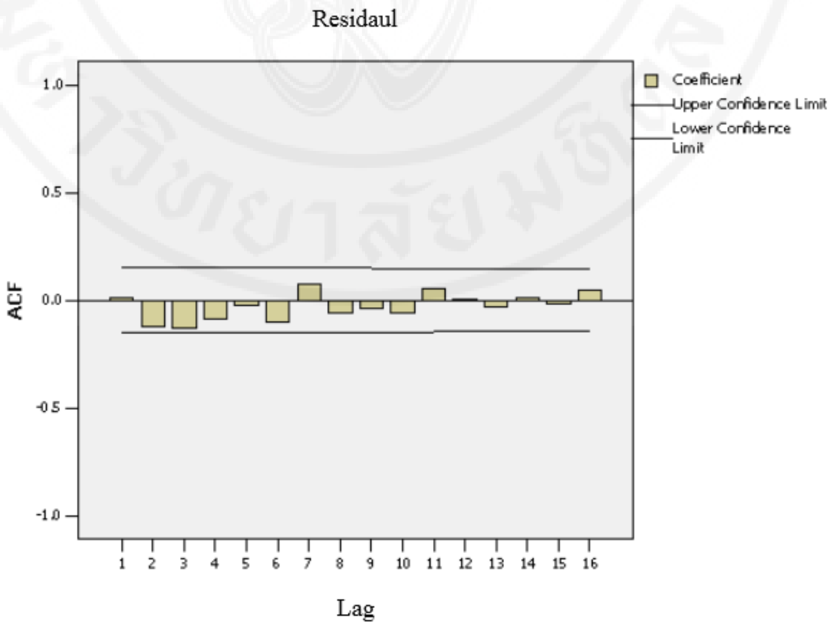


Figure 4.8 Autocorrelation test of residuals from forecasting.

From Figure 4.8, it is Autocorrelation test of residuals from forecasting model. Regarding to the graph, the model has correctness from Autocorrelation test, because there is not outside from the confidence intervals or the occurred residuals are not related to the previous residuals.

2) Correlation between Residuals and Input

Determining to the correctness of model by observing Correlation between Residuals and Input is shown in Figures 4.9 - 4.10.

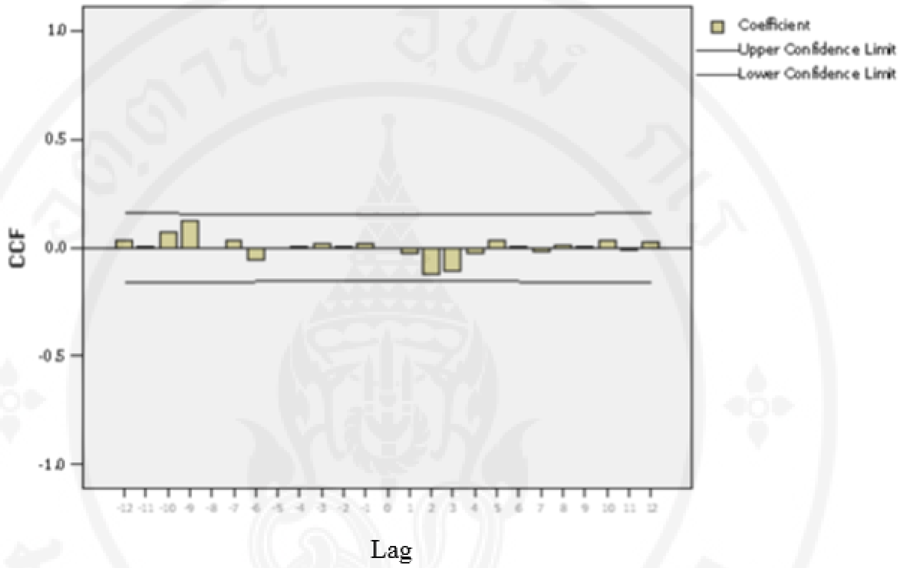


Figure 4.9 Correlation test between Residuals and Vessels.

From Figure 4.9, it can be described that the occurred residuals are not related to the vessels.

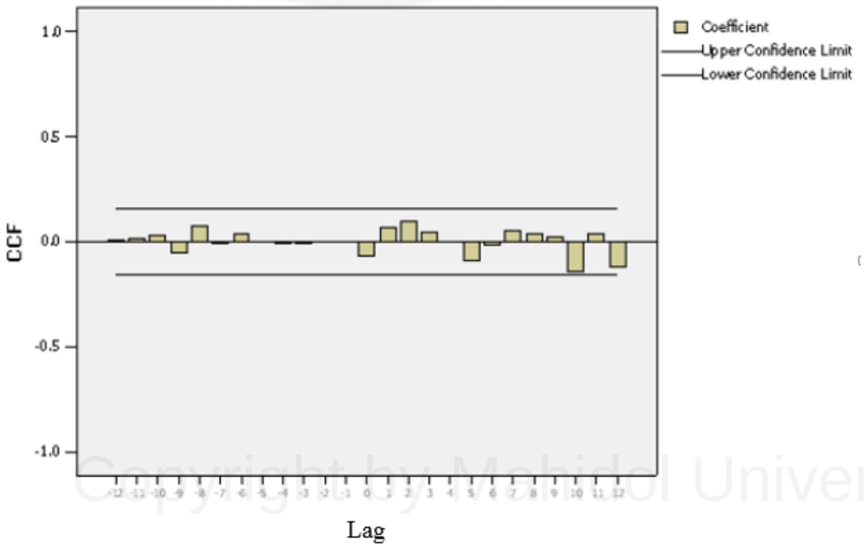


Figure 4.10 Correlation test between residuals and forecasting container.

From Figure 4.10, it can be described that the occurred residuals are not related to the forecasting container.

From Figures 4.8 - 4.10, the graph is show that the residuals are not related to the pair of test. Therefore, the created model has correctness in correlation test among 2 sets of time series.

4.4 Conclusion of research

The conclusion of results at the beginning of chapter is found that when the created model is verified the accuracy, it can be indicated that the model is able to verify the correctness statistically with 95% confidence intervals, which is considered that the model has the ability to be practical. The models used for forecasting the container with 3 methods, NARX is a method for the slightest error, ANN and SVR methods have MAPE value only 3.5%, 4.2% and 6.7% respectively, when they are compared to the actual value of containers. All of them will be concluded the overall as shown in Chapter 5.

CHAPTER V
CONCLUSIONS

This research aimed to create the model of forecasting monthly container. The result from analysis can show the accuracy and correctness in forecasting. Finally, the result from research can be concluded as follows:

5.1 The conclusion of research

This research is to study the correlation of related factors to the container for forecasting the container of Bangkok Port. The relevant factors used for study were the inward and outward of vessels in Bangkok Port affected on forecasting the container with the statistical test at 95% confidence intervals.

Regarding the experiment, the model is created for forecasting the container during the period from October 2006 to June 2014 or 94 months. For the accuracy and efficiency test on forecast model, it will be analyzed to find out the correlation of model and compare the model used for forecasting the container by the nonlinear autoregressive network with exogenous inputs (NARX), Artificial Neural Network (ANN) and the Support Vector Regression (SVR)

The results from forecasting the container which are verified the accuracy with 3 methods was found that MAPE value from NARX, ANN, and SVR are given as 3.5%, 4.2%, and 6.7%, respectively; however, NARX was the best method of all. When the model was compared to the truth value, it is very similar or not more than ± 5%. Moreover, after verifying the model, it has the correctness on the normal independence of residuals with 95% confidence intervals.

Using nonlinear model is the benefit to forecasting, because it would have accuracy and fitness to forecasting with the highest accuracy.

5.2 Recommendation for further development in the future

5.2.1 To improve and to be investigated the forecast model based on NARX with multiple inputs and multiple outputs (MIMO) to forecasting the container in advance.

5.2.2 To study the problems of the fuel usage forecast for the future.

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APPENDIX

DATA USED IN CREATE MODEL AND EXPERIMENTAL OUTPUT

MONTH	Model			
	Actual	ANN	SVR	NARX
Oct-06	130870	-	-	-
Nov-06	131504	-	-	-
Dec-06	130413	127743.8	117995.4869	141215.9
Jan-07	120199	114773.2	113796.8874	124076.6
Feb-07	123279	115022.8	113796.8874	125409.6
Mar-07	135904	138654.5	123001.3	137685.8
Apr-07	115333	116046.9	113796.8874	117967.9
May-07	121715	114864.4	113796.8874	118706.9
Jun-07	126415	114763.9	114413.1839	124289.2
Jul-07	133815	134290.7	121027.7567	135419.7
Aug-07	125072	125575.5	113796.8874	131978
Sep-07	124232	118395.9	113796.8874	123978
Oct-07	133054	128456.4	120343.1986	123095.4
Nov-07	138617	139975.4	125489.5829	131147.2
Dec-07	137846	144386.2	124760.033	140287.2
Jan-08	97197	114950.9	107429.7159	105252.9
Feb-08	111977	114595.5	113796.8874	112935.5
Mar-08	132926	134868.7	120306.2548	115939.3
Apr-08	116416	111866.9	113796.8874	116514.1
May-08	120083	115062.8	113796.8874	119850.5
Jun-08	115113	114758.5	113796.8874	119207.3
Jul-08	125586	124580.4	113796.8874	125402.8
Aug-08	121920	121528.6	113796.8874	122422.2
Sep-08	89889	105795.4	99302.2435	95847.47

MONTH	Model			
	Actual	ANN	SVR	NARX
Oct-08	108213	106940.1	113796.8874	108297.6
Nov-08	115999	112282.9	113796.8874	116471.9
Dec-08	107015	105195	113796.8874	117877.1
Jan-09	96382	114727.8	106544.8084	98473.98
Feb-09	86246	91506.1	95319.3334	87380.87
Mar-09	117320	114344.4	113796.8874	117273.2
Apr-09	95849	100204.9	105939.801	96095.56
May-09	109165	114703.9	113796.8874	109459.9
Jun-09	113243	113681.5	113796.8874	129881.5
Jul-09	116678	123534.8	113796.8874	123923.6
Aug-09	120556	114905.4	113796.8874	122061.5
Sep-09	115432	111076.5	113796.8874	114780.1
Oct-09	117577	114924.1	113796.8874	120791.9
Nov-09	121924	117669	113796.8874	113876.4
Dec-09	116646	120765.6	113796.8874	124446.1
Jan-10	122309	114743.7	113796.8874	126179.1
Feb-10	113194	109890.6	113796.8874	127660.7
Mar-10	129627	128432.9	117243.5838	129344.2
Apr-10	113853	112956.7	113796.8874	115182.3
May-10	116467	115387.4	113796.8874	117154.4
Jun-10	115730	114701.4	113796.8874	119368.2
Jul-10	125134	123919	113796.8874	123450.4
Aug-10	130832	123048.9	118441.8442	129395
Sep-10	126026	122882.1	113987.8333	133457.3
Oct-10	139079	140391.7	125805.7508	135433.6
Nov-10	128892	126541.9	116655.018	126994.9
Dec-10	137005	136179.3	123918.2893	139060.1
Jan-11	126191	116911.3	114185.2034	123353.6
Feb-11	116527	119796.9	113796.8874	116229.6

MONTH	Model			
	Actual	**ANN**	**SVR**	**NARX**
Mar-11	144473	138870.8	130772.0134	116006.7
Apr-11	127710	123948.4	115506.1451	125526.6
May-11	114140	123743.5	113796.8874	117020.3
Jun-11	93520	114729.1	103411.7364	94409.73
Jul-11	105599	105125.8	113796.8874	105547.7
Aug-11	108314	114213.6	113796.8874	82611.46
Sep-11	108082	102193.6	113796.8874	96563.63
Oct-11	91782	97027.36	101414.3436	93025.48
Nov-11	62745	87511.98	69316.4586	64238.83
Dec-11	99845	85435.33	110339.1741	101559.3
Jan-12	100289	99994.85	110864.7571	100314.9
Feb-12	94772	86005.96	104696.5949	104490
Mar-12	116520	116413.8	113796.8874	117361.6
Apr-12	109402	108258.8	113796.8874	108328.4
May-12	117704	116399.2	113796.8874	117140.8
Jun-12	116661	114073.4	113796.8874	118099.2
Jul-12	119828	124123	113796.8874	120249.6
Aug-12	118079	123100.2	113796.8874	121334.4
Sep-12	118753	118645.2	113796.8874	119450.2
Oct-12	119828	120679.3	113796.8874	119168.9
Nov-12	118079	123384.1	113796.8874	122741.7
Dec-12	118753	113887.3	113796.8874	119450.2
Jan-13	120758	115010.1	113796.8874	119168.9
Feb-13	104737	106394.8	113796.8874	105615.8
Mar-13	128146	129330.5	115962.5414	127779.3
Apr-13	115031	122721.4	113796.8874	112290.3
May-13	131796	121561	119257.4085	129943.6
Jun-13	126809	125608.7	114803.8662	130538.5
Jul-13	130077	124387.9	117662.8725	138759.1

MONTH	Model			
	Actual	ANN	SVR	NARX
Aug-13	130062	124117.4	117661.2339	115906.6
Sep-13	124823	123955.3	113796.8874	130037
Oct-13	129066	131381.9	116737.6222	121025.8
Nov-13	126333	124213.9	114321.9121	129368.1
Dec-13	129914	130648.3	117581.0319	126446
Jan-14	115866	119959.4	113796.8874	136995
Feb-14	103468	101943.9	113796.8874	99109.85
Mar-14	136182	136911.9	123185.2311	132836.8
Apr-14	118249	124109.8	113796.8874	116116.1
May-14	130999	130743.5	118563.0309	131483.6
Jun-14	128828	130080.5	116533.073	128099.5
Jul-14	125827	124268.7	113881.2205	128782.7
Aug-14		124096.9	113796.8874	128401.1

MATLAB SIMULATION CODE

```
% Solve an Autoregression Problem with External Input with a NARX Neural Network
% Script generated by Neural Time Series app
%
% This script assumes these variables are defined:
%
%   Vessel - input time series.
%   Vessel - feedback time series.

X = tonndata(Vessel,false,false);
T = tonndata(Vessel,false,false);

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. NTSTOOL falls back to this in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Nonlinear Autoregressive Network with External Input
inputDelays = 1:2;
feedbackDelays = 1:2;
hiddenLayerSize = 10;
net = narxnet(inputDelays,feedbackDelays,hiddenLayerSize,'open',trainFcn);

% Choose Input and Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to feedback output
% For a list of all processing functions type: help nnprocess
```

```
% Customize input parameters at: net.inputs{i}.processParam
% Customize output parameters at: net.outputs{i}.processParam
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.inputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a particular
network,
% shifting time by the minimum amount to fill input states and layer
states.
% Using PREPARETS allows you to keep your original time series data
unchanged, while
% easily customizing it for networks with differing numbers of delays,
with
% open loop or closed loop feedback modes.
[x,xi,ai,t] = preparets(net,X,{},T);

% Setup Division of Data for Training, Validation, Testing
% The function DIVIDERAND randomly assigns target values to training,
% validation and test sets during training.
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
% The property DIVIDEMODE set to TIMESTEP means that targets are
divided
% into training, validation and test sets according to timesteps.
% For a list of data division modes type: help nntype_data_division_mode
net.divideMode = 'value';  % Divide up every value
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
```

```
% For a list of all performance functions type: help nnperformance
% Customize performance parameters at: net.performParam
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
% Customize plot parameters at: net.plotParam
net.plotFcns = {'plotperform','plottrainstate','plotresponse', ...
  'ploterrcorr', 'plotinerrcorr'};

% Train the Network
[net,tr] = train(net,x,t,xi,ai);

% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
```

```
%figure, plottrainstate(tr)
%figure, plotregression(t,y)
%figure, plotresponse(t,y)
%figure, ploterrcorr(e)
%figure, plotinerrcorr(x,e)

% Closed Loop Network
% Use this network to do multi-step prediction.
% The function CLOSELOOP replaces the feedback input with a direct
% connection from the outout layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
view(netc)
[xc,xic,aic,tc] = preparets(netc,X,{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(netc,tc,yc)
% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop form for as
% long as there is known output data, and then switch to closed-loop form
% to perform multistep prediction while providing only the external input.
% Here all but 5 timesteps of the input series and target series are used to
% simulate the network in open-loop form, taking advantage of the higher
% accuracy that providing the target series produces:
numTimesteps = size(x,2);
knownOutputTimesteps = 1:(numTimesteps-5);
predictOutputTimesteps = (numTimesteps-4):numTimesteps;
X1 = X(:,knownOutputTimesteps);
T1 = T(:,knownOutputTimesteps);
[x1,xio,aio] = preparets(net,X1,{},T1);
[y1,xfo,afo] = net(x1,xio,aio);
% Next the the network and its final states will be converted to closed-loop
% form to make five predictions with only the five inputs provided.
```

```
x2 = X(1,predictOutputTimesteps);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(x2,xic,aic);
multiStepPerformance = perform(net,T(1,predictOutputTimesteps),y2)
% Alternate predictions can be made for different values of x2, or further
% predictions can be made by continuing simulation with additional
external
% inputs and the last closed-loop states xfc and afc.


% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a timestep early.
% The original network returns predicted y(t+1) at the same time it is
given y(t+1).
% For some applications such as decision making, it would help to have
predicted
% y(t+1) once y(t) is available, but before the actual y(t+1) occurs.
% The network can be made to return its output a timestep early by
removing one delay
% so that its minimal tap delay is now 0 instead of 1.  The new network
returns the
% same outputs as the original network, but outputs are shifted left one
timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
view(nets)
[xs,xis,ais,ts] = preparets(nets,X,{},T);
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)
```



```
% Deployment
% Change the (false) values to (true) to enable the following code blocks.
```

```
% See the help for each generation function for more information.
if (false)
  % Generate MATLAB function for neural network for application
deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder tools, or
simply
  % to examine the calculations your trained neural network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x,xi,ai);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  x1 = cell2mat(x(1,:));
  x2 = cell2mat(x(2,:));
  xi1 = cell2mat(xi(1,:));
  xi2 = cell2mat(xi(2,:));
  y = myNeuralNetworkFunction(x1,x2,xi1,xi2);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
```

```
function [y1,xf1,xf2] = myNeuralNetworkFunction(x1,x2,xi1,xi2)
%MYNEURALNETWORKFUNCTION neural network simulation
function.
%
% Generated by Neural Network Toolbox function genFunction, 06-Feb-
2015 14:35:24.
%
% [y1,xf1,xf2] = myNeuralNetworkFunction(x1,x2,xi1,xi2) takes these
arguments:
%   x = 1xTS matrix, input #1
%   1 = 1xTS matrix, input #2
%   xi1 = 1x2 matrix, initial 2 delay states for input #1.
%   xi2 = 1x2 matrix, initial 2 delay states for input #2.
% and returns:
%   y = 1xTS matrix, output #1
%   xf1 = 1x2 matrix, final 2 delay states for input #1.
%   xf2 = 1x2 matrix, final 2 delay states for input #2.
% where TS is the number of timesteps.

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1_xoffset = 141;
x1_step1_gain = 0.019047619047619;
x1_step1_ymin = -1;

% Input 2
x2_step1_xoffset = 141;
x2_step1_gain = 0.019047619047619;
x2_step1_ymin = -1;

% Layer 1
```

b1 = [2.780671497481304;-1.7712872970730456;1.5462985402479377;-0.72871635494243558;0.025006128215720021;-0.26440003371822357;-0.54455498613318942;1.3054127789214649;-1.8968984803192839;-2.0480808012906095];

IW1_1 = [-1.0685656897527807 0.71612649870082734;2.2578518940796584 0.59609232841183957;-1.5172465230813383 -0.33092996953605464;1.2248196784798315 1.4177784132657543;-0.56722660227598254 -0.90656692417865303;-1.5608184615201284 1.162524789408903;-1.3813869090286479 1.5228371244092871;0.69626498410989435 -0.22825574870241616;-0.028408900544983861 0.64844480335101662;-0.95702007574849146 -1.5560157191264201];

IW1_2 = [-1.8076387302197006 0.58130659216148028;0.38910131714813079 -1.2104413938969214;1.9608663341388513 -0.46852713308763927;1.2393837761678579 -0.88797955862353728;-1.7468379229725739 0.78795283809284589;0.41884281039339522 -1.4659846783824833;0.017186354242415481 0.88443359958196255;-2.0415680659249329 1.1710116136118851;-1.1375171473851944 2.1172779675968649;-1.7929112981196798 0.096942180529272892];

% Layer 2

b2 = 0.87361557270987678;

LW2_1 = [-0.78761482106735448 -0.43301713238213191 0.60068548781180886 0.24266369782098496 0.21846120149245235 -0.5047290115323062 0.59774542026290167 -1.0239405103244654 -0.089260142898105271 -0.00040940172766233685];

% Output 1

y1_step1_ymin = -1;

y1_step1_gain = 0.019047619047619;

```
y1_step1_xoffset = 141;

% ===== SIMULATION ========

% Dimensions
TS = size(x1,2); % timesteps

% Input 1 Delay States
xd1 =
mapminmax_apply(xi1,x1_step1_gain,x1_step1_xoffset,x1_step1_ymin);
xd1 = [xd1 zeros(1,1)];

% Input 2 Delay States
xd2 =
mapminmax_apply(xi2,x2_step1_gain,x2_step1_xoffset,x2_step1_ymin);
xd2 = [xd2 zeros(1,1)];

% Allocate Outputs
y1 = zeros(1,TS);

% Time loop
for ts=1:TS

  % Rotating delay state position
  xdts = mod(ts+1,3)+1;

  % Input 1
  xd1(:,xdts) =
mapminmax_apply(x1(:,ts),x1_step1_gain,x1_step1_xoffset,x1_step1_ymin);

  % Input 2
```

```
        xd2(:,xdts) =
mapminmax_apply(x2(:,ts),x2_step1_gain,x2_step1_xoffset,x2_step1_ymin);

        % Layer 1
        tapdelay1 = reshape(xd1(:,mod(xdts-[1 2]-1,3)+1),2,1);
        tapdelay2 = reshape(xd2(:,mod(xdts-[1 2]-1,3)+1),2,1);
        a1 = tansig_apply(b1 + IW1_1*tapdelay1 + IW1_2*tapdelay2);

        % Layer 2
        a2 = b2 + LW2_1*a1;

        % Output 1
        y1(:,ts) =
mapminmax_reverse(a2,y1_step1_gain,y1_step1_xoffset,y1_step1_ymin);
      end

      % Final delay states
      finalxts = TS+(1: 2);
      xits = finalxts(finalxts<=2);
      xts = finalxts(finalxts>2)-2;
      xf1 = [xi1(:,xits) x1(:,xts)];
      xf2 = [xi2(:,xits) x2(:,xts)];
    end

    % ===== MODULE FUNCTIONS ========

    % Map Minimum and Maximum Input Processing Function
    function y =
mapminmax_apply(x,settings_gain,settings_xoffset,settings_ymin)
      y = bsxfun(@minus,x,settings_xoffset);
      y = bsxfun(@times,y,settings_gain);
      y = bsxfun(@plus,y,settings_ymin);
```

```
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n)
  a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x =
mapminmax_reverse(y,settings_gain,settings_xoffset,settings_ymin)
  x = bsxfun(@minus,y,settings_ymin);
  x = bsxfun(@rdivide,x,settings_gain);
  x = bsxfun(@plus,x,settings_xoffset);
end
```

FORECASTING CONTAINER SUPPORT STRATEGY OF BANGKOK PORT

The 1st Management and Innovation Technology International Conference (MITiCON2014)

or

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Pattaya, Thailand

Computer Institute of

Ramkhamhaeng University

IT Management Program, Faculty of Engineering,

Mahidol University

Management and Innovation Technology International Conference (MITiCON2014)
Pattaya, Thailand, December 17-19, 2014

FORECASTING CONTAINER SUPPORT STRATEGY OF BANGKOK PORT

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ABSTRACT

Containerization is one of the important factors in Thailand's economics. This paper is aimed to study about the forecast quantity of container in the Bangkok port. Moreover, the existing literature emphasizes about linear and non-linear method. The collection data is non-linear information. The model uses correlation of the quantity of container and the quantity of vessels. The non-linear method uses Nonlinear Auto-Regressive with exogenous input (NARX) for our model to predict the container volume. The results were measured by root mean squared error (RMSE) and mean absolute percent error (MAPE) of the proposed model and the actual value. The accuracy of the forecast is very important to management and strategic planning for the organization.

1. INTRODUCTION

International trade has been rapidly increasing. The most of world trade relies on maritime transport which is essentially up to 90% of the total quantity of international cargo, resulting in the growth in container transshipment markets. The key requirement of a transshipment hub is its strategic location, i.e. the site itself must be sufficiently central to serve a large sub-region, and allow container shipping costs to be minimized.

In the future, the countries in the region unite the ASEAN Economic Community: (AEC) which encourage trade and investment within ASEAN and between ASEAN and other regions around the world. Availability and capacity of the port in the region, it is one of the most important factors for AEC.

Certainly, international trade by the vessel is important. Each country which far away depends on Hub and Spokes e.g. transshipment is more popular. The mainline ship with big vessel will dock in the modern port. Then use the feeder ship to transport cargo to another vessel.

The Bangkok port has potential to be linked to coastal ports and other international ports. But the government has a policy to reduce the traffic of the port. It limits the amount of cargo through the port to 1.0 million twenty-equivalent unit (TEU). In fiscal year 2004, the Bangkok port has inbounded and outbound cargo volume of around 15.3 million tons classified as imports of 7.9 million tons (52 percent) and exports 7.4 million tons (48 percent). In this case classifieds by container imports 0.63 million TEUs (48 percent) and container exports 0.69 million TEUs (52 percent), including 1.32 million TEUs [1]. That exceeded the government limitation. In the future containers and cargoes have been likely to steadily increase.

The Bangkok port has prepared a plan to raise benefit, i.e. build more warehouses, build more vehicle parking, plan to build the commercial center, and establishment of regional ports management for linking all logistic systems. The Bangkok port has planned to reduce FCL (Full Container Load) to gain more LCL (Less than Container Load) because of LCL earn more income than FCL.

The quantity of containers depends on many factors. In this work study, about the quantity of vessels have relation to quantity of containers. The prediction model which builds from the quantity of vessels has relation to quantity of container. In this model just can predict the quantity of container in the future. In the past, many researchers have been interested in forecast. The method of prediction has famous to use is about linear and non-linear. Many researches have been compared about method of forecast. Every method depends on the data to forecast, i.e. a comparison of traditional and neural networks forecasting techniques for container throughput at Bangkok port [2]. In this paper data collected in non-linear form. Generally, the problem of the non-linear model cannot support many data inputs, difficult work. However, Nonlinear Auto-Regressive with exogenous input; NARX) is non- linear model able to solve.Therefore, the forecast accuracy the quantity of container in the Bangkok port is important.

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The forecast is just accuracy that means in the management and planning of the organization in the future. From the above accurate forecasts using in this research is nonlinear autoregressive network with exogenous inputs (NARX). NARX is method which accuracy and wide to used, i.e. Forecasting peak air pollution levels using NARX models [3] and Defining and applying prediction performance metrics on a recurrent NARX time series model [4].

Nonlinear auto-regressive models with exogenous inputs (NARX models) have proved to be versatile and useful empirical models for industrial processes. There are a wide variety of identification methods and model structures from which to choose; in all methods, however, key parameters are the model orders, which are the number of past outputs and inputs used in the model.

The Structured of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents the research methodology. Section 4 presents the result and give a discussion of the result. Finally, some conclusions are provided in Section 5.

2. NARX MODEL

Dynamic neural networks are good at time series prediction. The NARX is type of time series problem to predict future values of a time series from past values of that time series and past values of a second time series. This form of prediction is called nonlinear autoregressive with exogenous (external). The model could be used to predict future values. It could also be used for system identification, in which models are developed to represent dynamic systems.

The NARX model will provide better predictions than this input-output model, because it uses the additional information contained in the previous values. However, there may be some applications in which the previous values would not be available. Those are the only cases where you would want to use the input-output model instead of the NARX model [5].

NARX models are the non- linear generalization of the well-known ARX models, which constitute a standard tool in linear black-box model identification [6]. These models can represent a wide variety of nonlinear dynamic behaviors and have been extensively used in various applications. A NARX model is formulated as a discrete time input–output recursive equation:

$$y(t) = f(y(t-1), \ldots, y(t-n_y), \\ = u(t-1), \ldots, u(t-n_u)) + \varepsilon(t), \quad (1)$$

where $u(\cdot)$, $y(\cdot)$are the model input and output, n_y, n_u are the respective maximum lags, and $\varepsilon(t)$ is a noise term, generally assumed Gaussian and white. The optimal predictor form of this model is

$$\hat{\varphi}(t) = f(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots, u(t-n_u)), \quad (2)$$

where $\hat{\varphi}(t)$ denotes the one-step ahead prediction of $y(t)$. Depending on how function $f(\cdot)$ is represented and parameterized, different NARX model structures and, consequently, identification algorithms are derived, for the NARX architecture shown in Fig. 3, that is one time series as input and one time series as output [2].

The NARX can also be modeled by means of artificial neural networks. A huge literature is available on NN model theory and applications [7]. Here, only a brief description of NNs is presented. Neural networks are composed by simple connected elements (denoted as neurons) operating in parallel. Each neuron's output is obtained by filtering a weighted sum of its inputs through a usually nonlinear function, i.e., the so-called activation function. The weights associated with the network connections are tuned during the training (learning) phase in order to reduce a given cost function, such as MSE (or a modified cost function, as proposed in this paper. The neural network structure used in this study is a standard feed-forward neural network shown in Fig. 1. This kind of network computes a vector function $f_{NN} : R^Q \to R^L$ where Q and L are the dimensions of the input and output vectors of the net, respectively, the lth element of the vector function f_{NN} for the nth pattern ($v^n \in R^Q$) is defined as (M is the number of the neurons in the hidden layer)

$$f_{NN}(v^n) = af_2\left(\sum_{m=1}^{M}(OW_{l,m} \cdot a_m\right) + g_1, \quad (3)$$

$$a_m = af_1\left(\sum_{q=1}^{Q}(IW_{m,q} \cdot v_q\right) + b_m, \quad (4)$$

where af_1 and af_2 are two real continuous functions, called activation function of the hidden layer (af_1) and of the output layer (af_2). The matrices IW (M × Q) and OW (L × M) are the input and output weight matrix, respectively, and b (M × 1) and g (L × 1) vectors are the bias terms. Neural networks learn on a training data set, tuning the parameters IW, OW, b and g by means of the well-known Levenberg-Marquardt back propagation (BP) algorithm [8]. The choice of the best neural network weights has been done minimizing a selected cost function (RMSE or MAPE).

In the current study, NARX network is trained by Levenberg-Marquardt

For the prediction purposes, the neural network output prediction is $\hat{\varphi}(t+n)$ always expressed by a residual prediction error e as following in Fig. 2. [5].

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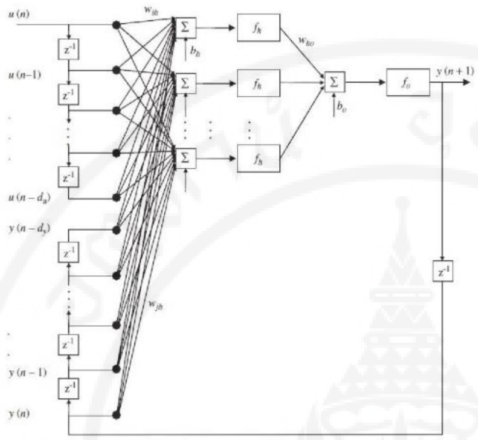

Fig. 1. The architecture of NARX neural network.

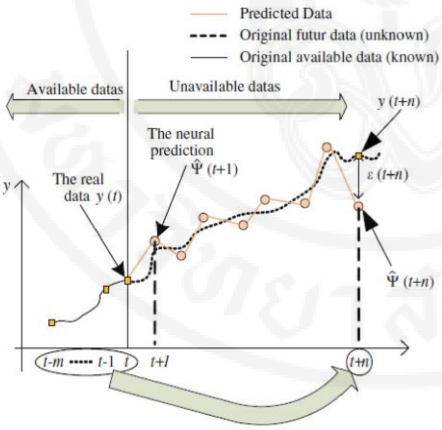

Fig. 2. Residual error obtained at each prediction.

In order to evaluate the prediction performance and compare it with the results reported in the literature, root mean squared error (RMSE) is calculated according to equation (5) and mean absolute percent error (MAPE) (6) as a measure of error.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)^2}, \quad (5)$$

$$MAPE = \frac{1}{N}\sum_{i=0}^{N}\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) x\ 100, \quad (6)$$

3. METHODOLOGY

3.1. Study area and data

This paper focuses only the Bangkok port. The sources of data are selected from historical data. The data set collected from the October 2006 – June 2014. The data have been 2 factors, quantity of vessel and quantity of container (TEU). In Fig. 3. shown the quantity of vessel and Fig. 4. shown the quantity of containers

3.2. NARX for forcasting the container quantity

The standard NARX network is a two-layer feed-forward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines to store previous values of the x (t) and y (t) sequences

In this model, the data will be entered into a non-linear function to forcast the quantity of container throughput at the port. The model uses parameter data is vessel and the data is input to the model to forecast the container quantity.

The input vectors and target vectors will be randomly divided into three sets as follows: 70% (94 records) will be used for training. 15% (66 records) will be used to validate that the network is generalizing and to stop training before over fitting. The last 15% (66 records) will be used as a completely independent test of network generalization.

The number of hidden layer neurons is set to 50. The default number of delays is 2.

This research uses the Levenberg-Marquardt method. Fig. 5. the network diagram for train.

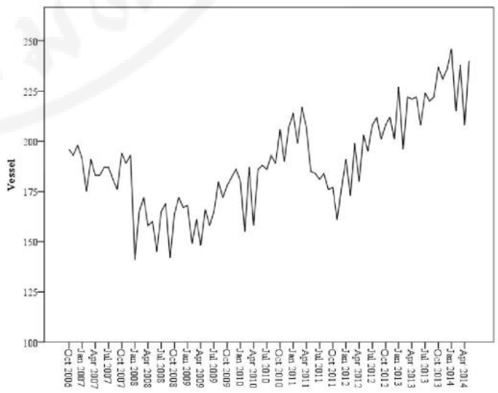

Fig. 3. The quantity of vessel.

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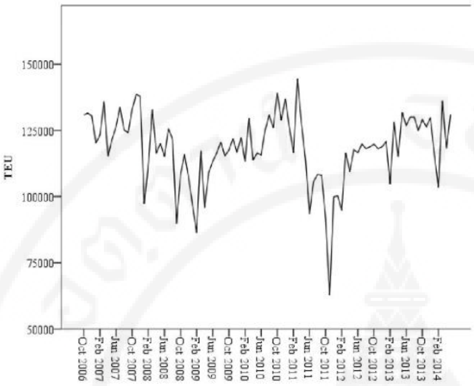

Fig. 4. The quantity of container (TEU).

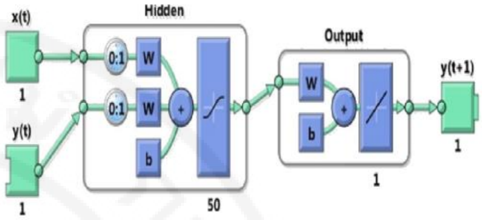

Fig. 5. Network diagram.

4. RESULTS

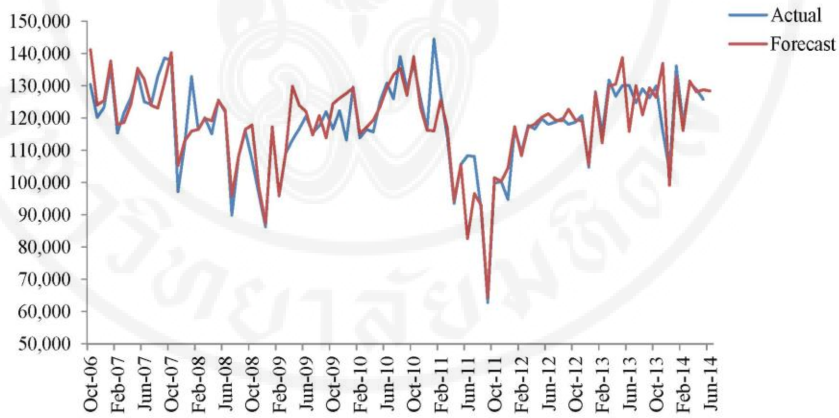

Fig. 6. The comparison of the actual and forecast quantity.

In this section presents that the result of forecasting the quantity of container. The results are shown in Fig. 6 the quantity of forecast and actual recorded container in monthly order. The trend of container had gone up since October 2011 until now the trend seems to go up.

The correlation coefficient is 0.529 that show relation between the quantities of vessel with the quantity of container.

When using the NARX to predict the quantities of container are presented accurately in Table 1. That the model performs significantly worse in term of the monthly accuracy (RMSE and MAPE).

Table 1. RMSE and MAPE of results.

	Performance
RMSE	6,887.28
MAPE	3.54%

5. CONCLUSION

The Bangkok port has with the increasing trend of the quantity of vessels and the quantity of containers. But the government's policy reduces the quantity TEU of the Bangkok ports and limits the amount of cargo through the port to 1.0 million. So that means Bangkok port loose change of business. Form the recorded every year has over maximum capacity. In the future the ASEAN Economic Community: (AEC). Which encourage trade and investment within ASEAN and between ASEAN and other regions around the world grew up. The Bangkok port should have management and planning for use this change to earning income.

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