An Application of Neural Networks for Forecasting Container Throughput at Bangkok Port

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Abstract-Containerization is a critical component for Thailand's economics. However, forecasts of container growth and development of Bangkok Port, the main port of Thailand, have been scant and the findings are divergence. Moreover, the existing literature emphasizes only two forecasting methods, namely time series and regression analysis. The aim of this paper is to explore the use of neural network for predicting future container throughput at Bangkok Port. The use of neural network is evident as a forecasting method for business firms and government offices but absent in predicting container throughput. Factors affecting cargo throughput at Bangkok Port are identified and entered into the neural network forecasting model that generates a projection of cargo throughput. Then the results are measured by root mean squared error (RMSE) and mean absolute error (MAE). Based on the results, this research provides a discussion on the application of neural network for forecasting container throughput.

Index Terms- Forecasting, Neural Networks, Container throughput

I. INTRODUCTION

Containerization is an important transportation system in the rapid growth of international trade, especially in the country dominating both of importing and exporting like Thailand. Containers are used for shipping many types of goods such as agricultural, consumer, and manufacturing products. The economic expansion increases the volumes of containers at Bangkok Port and the growth of this container throughput is one of the most important determinants of the large investment for container terminal. Therefore, the forecasting accuracy of the future throughput is crucial to both of private sectors and government offices for planning and managing their future development. Private sectors will enhance abilities for the growth of containers both of inbound and outbound. The governments' offices such as Port Authority, Customs Department and Marine Department will be able to improve daily port operations to serve the growth throughput and to increase productivity and the efficiency of the port. The numbers of containers are central to the planning and the operation of organizations and government transportation department at both micro and macro levels.

In 1994, forecast reports published by Japan International Cooperation Agency (JICA) [1] showed the forecasting volumes of import/export containers at Bangkok Port by using the technique of regression analysis on the two variables: population and Gross Domestic Product (GDP). Nevertheless, JICA's work has the limitation in presenting inadequate factors that would affect the forecasting accuracy of container throughput volume.

Nowadays, Bangkok Port Authority applies linear regression method and time series to forecast the number of containers in Bangkok Port. The factors adopted in this work [2] include GDP, exchange rate and world GDP. The weakness of this approach is the non-consideration of the regression on the relationship between the volumes of containers and the important macro-economic variables such as interest rate and inflation rate.

Many researchers have been interested in the relationship between factors of economics and the volumes of import and export. Dollar [3] studied the regression method to analyze the relationship between the outward orientation and per capita GDP growth. The results have implied that trade liberalization and exchange rate could improve growth performance in many poor countries. Greenaway and Nam [4] analyzed the various indicators of industrialization and macroeconomic. Ram [5] used a regression model to analyze the relationship between the exports and economic growth. Their study has confirmed the strong relationship of the export performance and the economic growth. Chou, Chub and Liang [6] presented the importance of the nonstationary relationship between the volumes of containers and the macro-economic variables. They used volumes of export containers, volumes of import containers, population, industrial production index, GNP, GNP per capita, wholesale GDP, agricultural GDP, industrial GDP and service GDP for the factors in the regression analysis.

This paper is based on the literature gap of the previous work from Peng and Chu [7]. They suggested neural network model for forecasting container throughput volumes in their paper after they applied six univariate forecasting models. Therefore the authors of this paper intend to explore the neural networks method for predicting the container throughput at Bangkok Port. The factors of consideration in this research include GDP, world GDP, exchange rate (compare to U.S. dollar), population, inflation rate, interest rate and fuel price.

The reasons of applying those factors are as follows:

1. Thailand's Key Economic Indicators are GDP, inflation rate, exchange rate and population [8], [9].

2. The factors affected to exporting are interest rate, fuel price, exchange rate and world GDP, and for importing are interest rate, exchange rate, population, inflation rate and GDP [8], [9].

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

II. LITERATURE REVIEW

A. Forecasting technique classification review

Forecasting serves many predicting information. It can help people and organizations planning in the future and making decisions [10].

There are basically three types of forecasting models: Time Series, Cause-and-Effect, and Judgmental [11], [12].

Time series: Time series is an ordered sequence of values of a variable at equally spaced time intervals. Predicting is continuous of historical pattern such as the growth in sale, gross national product or stock market analysis.

The example of time series methods are Autoregressive Moving Average (ARMA), Exponential Smoothing, Extrapolation, Linear Prediction, Trend Estimation, Growth Curve and Box-Jenkins. Time Series Analysis is used for many applications such as: Economic

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Forecasting, Sales Forecasting, Budgetary Analysis, Stock Market Analysis, Yield Projections, Process and Quality Control, Inventory Studies, Workload Projections and so on. Early attempts to study time series, particularly in the 19th century, were generally characterized by the idea of a deterministic world. It was the major contribution of Yule [13] which launched the notion of stochastic in time series by postulating that every time series can be regarded as the realization of a stochastic process.

ARIMA (Autoregressive Integrated moving average) were popularized by George Box and Gwilym Meirion Jerkins in early 1970s. The basis of the Box-Jenkins approach to modeling time series consists of three phases: identification, estimation and testing, and application. There are three types of ARIMA: univariate, dynamic or transfer function and VARIMA [14].

The other time series forecasting research, L.R.Weatherford and S.E.Kimes [15] used data from Choice Hotels and Marriott Hotels to test a variety of forecasting methods and to determine the most accuracy method. The methods are simple exponential smoothing, moving average methods, linear regression methods, logarithmic linear regression methods, additive, or pickup method, multiplicative method and Holt's double exponential smoothing. The result that five robust methods are suggested as exponential smoothing, pickup, moving average, Holt's method and linear regression.

The grain logistics system need forecasts of railroad grain carloads. Even though many forecasting studies have been conducted for vary application, but not have forecasting studies of quarterly railroad grain transportation have been published. Then Babcock and Lu [16] adopted time series model to forecast railroad grain transportations.

Because of not having the forecasting of quarterly barge grain transportation, Tang [17] intended to adopt a time series forecasting a quarterly model for Arkansas River soybean and wheat tonnage and estimate the two models.

Cause-And- Effect Model: The purpose of this model is to discover the form of the relationship and use it to forecast future the variable [14]. Regression Analysis, this model is used for several purposes, including data description, parameter estimation and control. Linear regression applications are adopted almost every fields, engineering, physical sciences, economics management and so on [18]. Non-linear regression, Wiener interested the ideas of functional series representation and further developed an existing material [19]. Gooijer and Kumar [20] provided an overview of the developments in this area to the beginning of the 1990s. These authors argued that the evidence for the superior forecasting performance of nonlinear models is patchy. Neural network is also cause-and-effect model, and can applied to many application but on the survey of 2006 neural network has not caught in business yet [12].

The econometric is an application statistical and mathematical method to predict economic data, such as interest rate, inflation and so on. This method is also for policy purpose [21], [22].

Qualitative Forecasting: This model does not require data in the same manner as quantitative forecasting methods and are mainly the product of judgment and accumulated knowledge.

Estimating method that relies on expert human judgment combined with a rating scale, instead of on hard (measurable and verifiable) data.

Qualitative techniques can be used in a wide range of circumstances. In some cases quantitative techniques cannot be used, e.g. when the past information about the values being forecast does not exist. For example, for a new product, there are no past data on sales on which to base estimates of future sales. These are often used in business are: (i) analog, Delphi method, diffusion, PERT (Performance Evaluation Review Technique), and survey. Qualitative methods consist of three kinds of data are open-end interviews, direct observation and written documents [11], [12], [23].

The several of application of qualitative forecasting such as, Kesh and Raj intend to develop a model for financial forecasting using the principles of qualitative reasoning. They purpose the illustration how qualitative reasoning models can be developed in a financial domain, the application of these models and the problems and issues related to the development of qualitative reasoning model for financial forecasting and decision making [24].

The studies in the literature on predictions of container volumes are not only in time series forecasting but also in neural network method. Wei and Yang applied artificial neural networks (ANNs) to study transit containers in Kaohsiung Port [25]. Lam, Seabrooke and Hui adopted neural networks (NN) method for forecasting Hong Kong Port cargo throughput [26], while Zhang and Kline used the NN approach to forecasting quarterly time series [27]. The next part will discuss about basic of neural networks and application.

B. Neural Networks

The main characteristic of a neural network is the ability to learn from environment, and to improve its performance through learning [28], [29]. Neural networks represent a recent approach to time series forecasting. There has been an increasing interest in using neural networks to model and forecast time series over the last decade, one of the most successfully applied technique in the financial domain [30].

The first research is adopted neural networks method for forecasting application as, Hu and Root [31] initiated the implementation of ANN on weather forecasting.

Neural network applications have employed to make better prediction about investment opportunities. ANNs are valuable tool for nonlinear time-series analysis and forecasting [32]. Integration TIA and Neural Networks integrate a powerful forecasting tool to add a learning component and allow that model to adjust to novel situations [33].

The result of forecasting by dynamic neural networks (DAN) is better than the traditional neural networks and autoregressive integration moving average (ARIMA) model [34].

H.S. Hippert, D.W. Bunn and R.C. Souza adopted neural networks model to forecast hourly electricity demands, and extend the apparent over-parameter affects their performance in a forecasting [35].

Support Vector Machine [SVM] can provide the best prediction performances, determine the network topology and estimate all the parameters automatically [36].

They conduct a simulated study and conclude that ANNs can be used for modeling and forecasting nonlinear time series, and nonlinear applications can be handled by using neural networks [37].

This research discuss for an application neural networks can achieve significantly higher numerical accuracy than more conventional techniques [38].

Zhang [39] proposed a neural ensemble model based on adding noises to the input data and forming different training sets with the jittered input data, jittered method is available for the single modeling approach with a variety of time series processes.

C. Traditional Statistics & Neural Networks

This part compares the accuracy of traditional forecasting and Neural Networks methods as, Skapura [29] indicate that neural nets are a useful approach to generalization problems in such non-conservative domains, performing much better than mathematical modeling techniques like regression.

Both researches presented by Surkan and Singleton [40, 41] compared the performance of the neural network to conventional, statistical methods to validate the network performance.

ANNs have three great advantages over traditional methods such as; universal approximation capabilities, recognize "on their own" implicit dependencies and relationship in data, learn" to adapt their behavior [30].

Heravi, Osborn and Birchenhall [42] found that the neural networks models have a clear advantage for forecasting the direction of the future annual growth for these series.

D. Forecasting evaluation and accuracy measures

There are several statistical methods available to evaluate forecast performance. The commonly used forecast accuracy measures are; Mean Error (ME), MSE (Mean squared error), RMSE (Root mean squared error), MAPE (Mean absolute percentage error) and so on [11].

Mahmoud [43] mainly focused on comparisons of the accuracy of these techniques. The comparisons cover both quantitative and qualitative methods. In addition the summary includes studies seeking to test or improve accuracy by combining forecasting techniques [43].

The original M-competition, measures used included the MAPE, MSE, AR, MdAPE, and PB. The MAPE also has problems when the series have values close to (or equal to) zero [11]. The other study which looked at forecasting telecommunications data, used MAPE, MdAPE, PB, AR, GMRAE, and MdRAE, taking into account some of the criticism of the methods used for the M-competition [44].

Agami, Atiya, Saleh and El-Shishiny [33] used MSE and MAD values as the two criteria for assessing accuracy of the models. The

comparative assessment against the traditional ANN and ARIMA models shows dynamic neural networks (DAN) to perform uniformly better than other methods, and Hippert, Bunn, Souza [35] also measured the accuracy by MAE and RMSE.

This section, we wish to present the knowledge of forecasting technique and neural network method. The comparison of tradition forecasting and Neural Networks methods are compared. The last topic is the accuracy of the forecasting. This is an importation point for measurement. The next section will present the methodology of this work.

III. RESEARCH METHODOLOGY

ANNs have been shown to be a successful as predictive tools in variety of the ways as financial, weather, sport outcomes and so on. Neural networks are predictive models based on the action of biological neurons. Neural Networks method as Multilayer Perceptron (MLP) is adopted in this paper to forecast number of containers throughput in Bangkok Port. ANNs must be trained with a sizable number of example of past patterns [45],[46]. The interval activity of the neuron can be shown in figure 1,

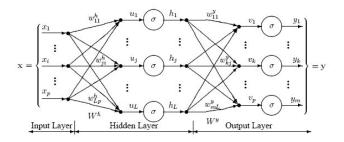


Figure 1: The Multilayer Perceptron Neural Network Model

Input Layer: A vector of predictor variable values (x1...xp) is presented to the input layer. The input layer distributes the values to each of the neurons in the hidden layer.

Hidden Layer: Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (wji), and the resulting weighted values are added together producing a combined value uj.

Output Layer: Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (wkj), and the resulting weighted values are added together producing a combined value vj.

Training process: The goal of the training process is to find the set of weight values that will cause the output from the neural networks to match the actual target values as closely as possible.

Let x(i) denote the input vector x for the ith case used to train the network, and the weights before this case is presented to the net by the vector w(i). The updating rule is w(i+1) = w(i)+ $\eta(y(i)-y(i))x(i)$ with w(0) = 0.

The process of training and testing for forecasting container throughput at Bangkok port

Step 1 Set parameter

- Step 2 Read input
- Step 3 Read weight1, input and hidden
- Step 4 Read weight2, hidden and output
- Step 5 Computation1, input and hidden
- Step 6 Computation2, hidden and output

Many researchers analyze the relationship of economic factors, the volume of imports and exports as, Dollar [3] analyzed the relationship between the outward orientation and per capita GDP growth. Greenway [4] studied indicators of industrialization and macro-economic. Ram [5] analyzed the relationship between the exports and economic growth and Chou, Chub and Liang [6] forecasted the volumes of Taiwan's import containers, population, industrial production index, GNP, GNP per capita, wholesale, GDP, agricultural GDP, industrial GDP and service GDP.

The data sets are adopted in this research. We accumulated data of factors and number of containers from 1999 until 2009 (by monthly), and factors are impacted to this research such as population, GDP,

world's GDP, exchange rate, interest rate, inflation rate, fuel price. These factors are applied to the research because all of them are Thailand's Economic indicators and the others affect to both of importing and exporting.

The scope of this work is forecasting the container throughput only in Bangkok Port. In this study, we consider two accuracy measurements to the neural networks model. They are the root mean squared error (RMSE) and the mean absolute error (MAE) defined as follows:

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{n}$$
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{n}}$$

Note, Yi and Y^{$\hat{}$} are the actual and the predicted values of the time series in period i, respectively. Obviously, both of measures are positive in value and the smaller the value obtained for each of the measures calculated, the better the performance of the forecasting method.

The quantity r, called the *linear correlation coefficient*, measures the strength. The value of r is between $-1 \le r \le +1$. The + and - signs are used for positive correlations and negative correlations, respectively.

Positive correlation: If x and y have a strong positive linear correlation, r is close to +1. An r value of exactly +1 indicates a perfect positive fit. Positive values indicate a relationship between x and y variables such as values for x increase, values for y also increase.

IV. RESULTS AND DISCUSSION

This section presents the results of the neural network model for forecasting container throughput and gives the discussion of the results. The results from the model are shown in Figure 2 illustrating the actual and predicted number of container throughput volumes in monthly order. The trend of the container throughput had gone up since 1999 until the year 2008 the trend seems to go down because of the effect of the world's economic crisis.

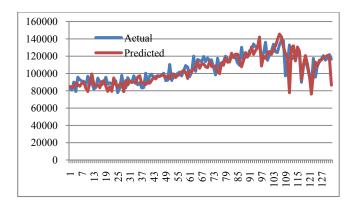


Figure 2: The comparison of actual and predicted container throughput volumes of Bangkok port (unit: TEU)

When using the neural network to predict container throughput volumes for import and export, the factors discussed in Section III were analyzed to find the relationship of the factors to the number of exporting and importing. From the analysis, the world's GDP, interest rate, exchange rate, population and interest rate affect to the export volumes. On the other hand, fuel price and interest rate affects to the cost of productions which mean the factors affected to the volumes of import include interest rate, exchange rate, population, inflation rate, fuel price and GDP. Applying these factors in the neural networks for predicting import and export container volumes, the predicted container throughput volumes are presented in Table 1. Proceedings of the World Congress on Engineering 2010 Vol I WCE 2010, June 30 - July 2, 2010, London, U.K.

Table 1: Actual and predicted container throughput volumes of Bangkok port unit: TEU.

Month	Year	Actual	Predicted	Month	Year	Actual	Predicted
1	1999	82924	84902.93	1	2003	91787	95747.93
2	1999	80702	84300.51	2	2003	92197	97237.01
3	1999	90046	83480.91	3	2003		94092.52
4	1999	79139			2003	91913	99339.40
			89245.94	4			
5	1999	95726	87090.49	5	2003	96721	99447.26
6	1999	92711	85220.18	6	2003	97169	95276.20
7	1999	91231	88928.87	7	2003	100204	97830.68
8	1999	90807	89792.18	8	2003	101589	98678.52
9	1999	85582	83076.27	9	2003	97187	101756.47
10	1999	96782	79190.70	10	2003	102995	103656.88
11	1999	87746	88992.44	11	2003	109150	101312.62
12	1999	89269	99393.35	12	2003	107335	94199.52
1	2000	81982	87523.85	1	2004	96237	103020.61
2	2000	83859	85030.57	2	2004	101520	102041.55
3	2000	94587	87157.23	3	2004	119967	105531.45
4	2000	90370	83497.32	4	2004	102557	107476.91
5	2000	87054	90529.63	5	2004	116205	113661.52
6	2000	89338	91686.09	6	2004	115039	105995.03
7	2000	95603	85317.01	7	2004	113598	110845.56
8	2000	87681	79376.57	8	2004	119569	111201.91
9	2000	89224	84683.34	9	2004	113880	107700.03
10	2000	88013	79363.47	10	2004	117804	106858.11
11	2000	89947	94879.34	11	2004	114975	113710.63
12	2000	91581	87129.15	12	2004	115784	108185.11
1	2001	77895	84149.68	1	2005	106872	107445.37
2	2001	83468	87440.40	2	2005	98332	108881.37
3	2001	97814	88927.94	3	2005	117477	102101.40
4	2001	84532	79010.51	4	2005	105557	99880.68
5	2001	83480	91824.91	5	2005	109890	112526.00
6	2001	95165	86760.45	6	2005	114128	109568.10
7	2001	90936	91388.98	7	2005	119988	118142.55
8	2001	89479	89918.31	8	2005	117046	112993.12
9	2001	97250	90313.24	9	2005	113322	113461.65
10	2001	92552	88555.36	10	2005	121011	123373.72
11	2001	87033	96158.85	11	2005	118935	118367.54
12	2001	89575	97405.27	12	2005	118177	122338.66
1	2002	83294	88521.66	1	2006	112398	122287.95
2	2002	83683	89315.98	2	2006	109398	114463.27
3	2002	100242	87132.46	3	2006	130177	107773.58
4	2002	88750	90300.20	4	2006	115790	114933.46
5	2002	97428	88787.01	5	2006	119539	124205.50
6	2002	99141	92211.98	6	2006	118972	119561.14
7	2002	94755	95700.66	7	2006	126234	122212.00
8	2002	96587	93794.55	8	2006	126697	130802.13
9	2002	97521	96451.71	9	2006	134128	122128.57
10	2002	96703	96768.00	10	2006	130870	126429.84
11	2002	97899	98236.04	11	2006	131504	130275.67
12	2002	100290	97608.28	12	2006	130413	142165.10

Table 1: Actual and predicted container throughput volumes of Bangkok port unit: TEU. (cont.)

Month	Year	Actual	Predicted	Month	Year	Actual	Predicted
1	2007	120199	108659.10	7	2008	125,586	130577.54
2	2007	123279	119975.51	8	2008	121920	125788.37
3	2007	135904	117625.09	9	2008	89889	92987.38
4	2007	115333	123451.82	10	2008	108213	110322.68
5	2007	121715	125440.92	11	2008	115999	120588.64
6	2007	126415	122197.46	12	2008	107015	110388.95
7	2007	133815	128113.45	1	2009	96382	97931.05
8	2007	125072	131898.22	2	2009	86246	76211.68
9	2007	124232	138883.73	3	2009	117320	99922.30
10	2007	133054	145538.39	4	2009	95849	113072.59
11	2007	138617	142512.28	5	2009	109165	108434.16
12	2007	137846	130544.75	6	2009	113243	115288.95
1	2008	97197	122868.88	7	2009	116678	115594.75
2	2008	111977	118293.79	8	2009	120556	118107.62
3	2008	132926	77778.85	9	2009	115432	119333.96
4	2008	116416	130053.19	10	2009	117577	120801.51
5	2008	120083	132000.23	11	2009	121924	119004.29
6	2008	115113	114578.65	12	2009	116646	86557.55

The results of the neural network forecasting are presented in Table 2. The number correlation coefficient describes the relationship of factors and the container volumes. The correlation coefficient of import and total volumes are pretty high at 0.86 and 0.84 respectively while those factors can explain the relationship of export container volumes at 0.78.

Table 2: Performance of forecasting number of container

Item	Import	Export	Total
Correlation coefficient	0.86	0.78	0.84
Mean absolute error (MAE)	4075.46	3406.22	7246.93
Root mean squared error (RMSE)	5107.89	4589.82	11598.85
Total Number of Instance	132	132	132

V. CONCLUSION

It is very important for the government body and private organizations to predict the volumes of container throughput at Bangkok Port. The forecast number will enable Bangkok Port Authority manage and develop the main infrastructures and equipments for supporting the country's competitiveness. Moreover, Bangkok Port Authority will be able to cooperate with the government and private sectors to invest for port business in order to serve transportation system and facilities for customer satisfactions, to ensure optimum efficiency and fairness of port services. The result of this study contributes to the knowledge of what factors are important and affect to the import and export container volumes. The forecasting accuracies are satisfactory and the values of correlation coefficients are more than 75%. The accuracies of predicting are evaluated by calculating MAE and RMSE. In this research, neural networks are one of valuable tools for nonlinear time-series analysis and forecasting. In the future, it may be worthwhile to explore other forecasting methods as times series methods to compare to the latest technologies as neural networks for predicting container throughput volumes.

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