Modelling and Forecasting for Automotive Parts Demand of Foreign Markets on Thailand

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Abstract

Thailand's export of automotive parts to foreign markets increases in value greatly each year. Within this group, the wheels, including parts and accessories (WPA) exported to foreign markets are of the greatest value to manufacturers who need to be aware of the demand in advance. The objective of this research is to find an accurate forecasting model for predicting advanced demand for the WPA and calculate the optimal quantity for export by using a linear programming (LP) model in order to benefit from the maximum profit. The methodology is selection and analysis in a performance of time series forecasting models (naïve, moving average, single exponential smoothing, and exponential smoothing with trend) and an artificial neural networks (ANNs) model in forecasting the WPA exported from Thailand. The countries with the five top highest demands for the number of WPA are: Japan, China, South Korea, Germany, and Indonesia. The demand data of five countries is used for analysis and the data was collected during the period of 1997 to 2008. The mean absolute percentage error (MAPE) is used as a measure of forecasting accuracy. The results reveal that an ANNs model outperforms the other models for Japan, Germany, and Indonesia, whereas an exponential smoothing with trend is close to the actual demand for China. There are, however, no accurate forecasting models for South Korea because the five models give an error greater than 50%. The accurate forecasting model for each country is used to forecast the advanced demand. After that the forecasting results are used for finding the optimal quantity for exporting to the five countries by using the LP model in order to receive maximum profit. The results of this research can be used for effective production planning or investment by informing manufacturers.

***Keywords**: Modelling and forecasting, Automotive parts, Time series forecasting, Artificial neural networks, Linear programming*

1 Introduction

According to Thai Government policy, the automotive industry, which is the strategic industry of Thailand, has been promoted to be an automotive production centre of South-East Asia or Detroit of Asia by promoting sales in both domestic and foreign markets, supporting automotive parts research and development and establishing an automotive parts testing centre [1]. Consequently, the automotive companies have moved their factories into Thailand in order to use as a base of export [2]. Those events have provided advantageous for the Thai automotive industry, so the automotive parts industry and automotive industry have grown up together. Nowadays, there are about 1,667 entrepreneurs of the automotive parts industry in Thailand. About 90,000 employees are retained by those factories. Most entrepreneurs are small and medium enterprises (SMEs) which accounts for about 1,641 entrepreneurs or 98.44% of all entrepreneurs. There are 2,242 factories of which 2,160 are medium and small factories, or 96.34%, and large factories 3.66%.

In 2008, the Thai automotive parts industry was affected by a world economic problem. In 2009, the world economic crisis was forecast to be more serious. Automotive industries around the world encountered very serious problems, especially a lack of liquidity of the automotive industry in the USA, which is waiting for government help. Now, main automotive producers in every region have announced a decrease in the numbers of employees, production, and investment. Moreover, the situation affects the direction of the automotive parts industry, especially the type of original equipment manufacturing (OEM) which is within the automotive production system of those automotive companies. In 2009, it is expected that the Thai automotive production may decrease greatly, which could in turn diminish the Thai automotive parts production in the type of OEM seriously. Thai automotive parts entrepreneurs may encounter several pressure conditions, so they have to discover new strategies for opportunity and run their business in a stringent economic crisis.

The Thai automotive parts industry exporting to foreign markets shows that the WPA are of the greatest export value. The countries with the five top highest demands for the number of WPA are: Japan, China, South Korea, Germany, and Indonesia. This research involves the historical, collected demand data during the period from 1997 to 2008. Figure 1 shows the demand of WPA for the five countries. The reason for this research is that manufacturers need to know in advance the demand by the foreign markets. The objective of this research is to forecast the advanced demand for the WPA by an accurate forecasting model. In addition, the forecasting results are used for finding the optimal quantity for exporting to five countries by using the LP model in order to gain maximum profit. This research is organised as follows. Section 2 illustrates some relevant literature. Section 3 describes the research methodology, the background of the forecasting models and the measure of forecasting error used in this research. Section 4 shows the results. Section 5 gives an illustrative example with the application of the LP model. Section 6 presents some conclusions and recommendations from this research.

2 Literature review

In the literature, there are several researches that relate to the forecasting or comparison of the forecasting models. The exported rice forecasting uses an exponential smoothing model, autoregressive integrated moving average (ARIMA) model, and artificial neural networks (ANNs) model for the comparison of forecasting model accuracy with mean absolute percentage error (MAPE). The result shows that the back- propagation neural network model is the lowest MAPE compared with Holts-Winters and Box-Jenkins model [3]. There is research about the forecasting of touring demand for the tourist industry. It aims to predict the number of tourists who would go to Hong Kong by comparison with a moving average model, a single exponential smoothing model, Holt's exponential smoothing model, regression model, and artificial neural networks model. The result shows that the artificial neural networks model and the single exponential smoothing models are more accurate than the other models. The accuracy of these models is compared with MAPE [4].

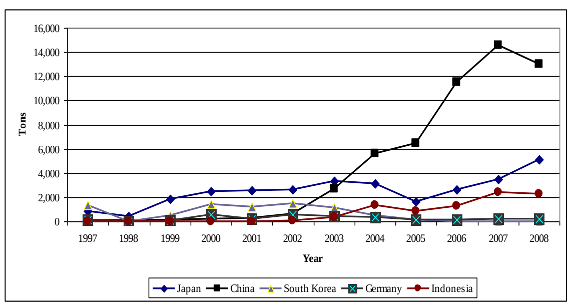

Figure 1: The demand of wheels, including parts and accessories (WPA) for the five countries

Artificial neural networks have a universal and highly flexible function; they can be applied in the fields of science and engineering. In recent years, neural network applications in finance for such tasks as pattern recognition, classification, and time series forecast have dramatically increased. The large numbers of parameters, however, that must be selected to develop a neural network forecasting model, has meant that the design process still involves much trial and error. It is to provide a practical introductory guide in the design of a neural network for forecasting economic time series data [5]. There is research which applies the mathematical models to the planning of production for presenting the highest usefulness beneath the product quantity, the limitation of producing ability and the limitation of inventory. This research creates the mathematical models in linear programming with the principle of planning of production and inventory system management to conform to each condition and appropriate planning of production [6].

According to the papers above, the researches show that ANNs model is the accurate forecasting model by comparing with the time series models. Most researches do not offer a forecast about the automotive industry or the automotive parts industry. This research is interested in finding the forecasting model by using time series models and an ANNs model. The accurate forecasting model is used for forecasting the WPA exported to foreign markets.

3 Research methodology

This research is to forecast the advance demand by the accurate forecasting model. The methodology is selecting and analyzing the performance of traditional forecasting models (naïve, moving average, single exponential smoothing, and exponential smoothing with trend) and an artificial neural networks (ANNs) model in forecasting the WPA exported from Thailand. In the preliminary process, the procedure is the data collection of WPA: after that they are plotted for finding characteristics of data that have trend, seasonal, cyclical, and random. These components are characteristic of time series [7]. The time series models use the past data for future forecasting whereas in the part of ANNs model, it uses the input variables which affect the forecasting values. The results from the time series models and ANNs model are compared for accuracy of forecasting the demand for finding the accurate forecasting model. Lastly, the use of the LP model finds the optimal WPA quantity of each country for maximum profit. The procedure of the research model is illustrated in Figure 2.

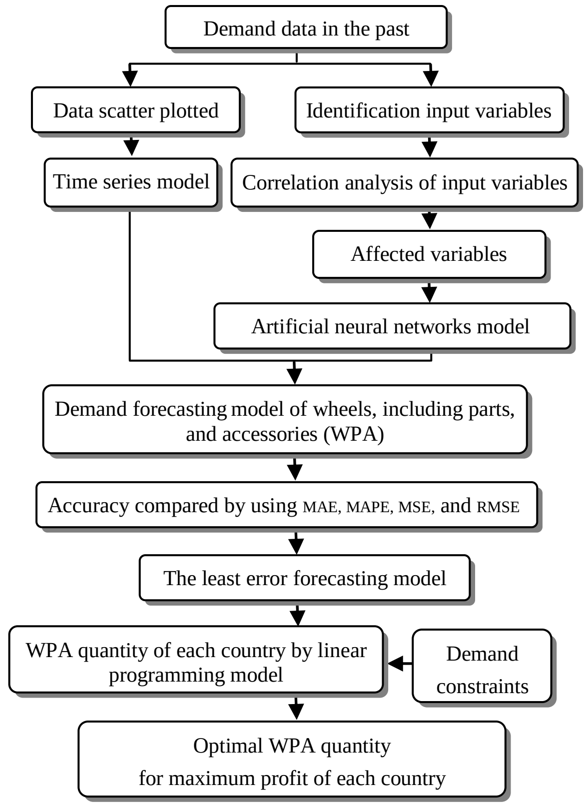

Figure 2: Procedure of research model

3.1 *Data and variables*

This research uses data from secondary sources for forecasting model estimation during the period 1997 to 2008. The data is obtained from the following sources of government services, private companies and others such as:

- Customs Department
- Thailand Automotive Institute
- The Office of Industrial Economics
- Department of Export Promotion
- Thai Autoparts Manufacturers Association

3.2 *Modelling for forecasting*

Forecasting is a prediction of what is likely to happen in the future by using the available data. The forecasting usually considers by judgment [8]. There are many forecasting techniques that can be classified into four main groups: (1) Qualitative methods are primarily subjective; they rely on human judgment and opinion to make a forecast. (2) Time series methods use historical data to make a forecast. (3) Causal methods involve assuming that demand forecast is highly correlated with certain factors in the environment (e.g., growth rate of GDP, foreign exchange rate). (4) Simulation methods imitate the consumer choices that give to demand to arrive at a forecast [9]. This research uses time series forecasting techniques by assuming that something which occurred in the past will recur. The advantages of time series forecasting approaches are that they are simple to apply. The only important factor is time. The time series models are used as naïve, moving average, exponential smoothing, and exponential smoothing with trend [10].

3.2.1 Naïve method

The naïve method is the simplest for forecasting [11]. It uses the latest demand for forecasting the next period. The model for the naïve method is:

$$F_{t+1}^{c} = A_{t}^{c} \tag{1}$$

Where

F_{t+1}^{c} = Demand forecasting at time period $t+1$

A_{t}^{c} = Actual demand at time period t

t = Time period as yearly

c = The country such as Japan, China, South Korea, Germany, or Indonesia

3.2.2 Moving average

A moving average model is used to forecast the next period by using a number of historical actual data values to generate a forecast. It gives equal weight to all of the past values. The forecasting by moving average model that the important factor is a number of periods (n) as yearly start at $n = 2$ to $n = 4$. A moving average model can be calculated by:

$$F_{MA(n),t+1}^{c} = \frac{1}{n}\left(\sum_{t=i+1-n}^{i} A_{t}^{c}\right) \tag{2}$$

Where

$F_{MA(n),t+1}^{c}$ = Demand forecasting in moving average n

$t+1$ = Period at forecast

i = The last period for calculation

t = The first period in start for calculation

n = Number of periods in moving average as yearly

In this research, the number of periods (n) in moving average is 2, 3, and 4 years.

3.2.3 Single exponential smoothing

A single exponential smoothing model allows us to vary the importance of recent demand to the forecast. It can be calculated by:

$$F_{ex,t+1}^{c} = \alpha_c A_{t}^{c} + (1-\alpha_c) F_{ex,t}^{c} \tag{3}$$

Where

$F_{ex,t+1}^{c}$ = Demand forecasting in single exponential smoothing in period $t+1$

$F_{ex,t}^{c}$ = Demand forecasting in single exponential smoothing in period t

α_c = The smoothing constant such that $0 < \alpha_c < 1$

It starts with $\alpha_c = 0.1$ until $\alpha_c = 0.9$ for each country.

3.2.4 Exponential smoothing with trend

As an extension of the single exponential smoothing approaches by assuming the existence of a trend.

$$F_{aex,t+1}^{c} = F_{ex,t+1}^{c} + T_{ex,t+1}^{c} \tag{4}$$

However, we can calculate $T_{ex,t+1}^{c}$ by formulation:

$$T_{ex,t+1}^{c} = \beta_c \left(F_{ex,t+1}^{c} - F_{ex,t}^{c}\right) + (1-\beta_c) T_{ex,t}^{c} \tag{5}$$

Where

$F_{aex,t+1}^{c}$ = Adjusted exponential smoothing forecasted demand in period $t+1$

$F_{ex,t+1}^{c}$ = Demand forecasting in single exponential smoothing period $t+1$

$T_{ex,t+1}^{c}$ = Exponentially smoothing trend factor in period $t+1$

$F_{ex,t}^{c}$ = Demand forecasting in single exponential smoothing in period t

$T_{ex,t}^{c}$ = Exponentially smoothing trend factor in period t

β_c = Smoothing constant $0 < \beta_c < 1$

It calculates by changing α_c and β_c for each country. The smoothing constant (β_c) must take a value between zero and one same as the alpha (α_c). The exponential smoothing with trend, it starts with $\alpha_c = 0.1$ until $\alpha_c = 0.9$ and β_c starts with 0.1 until 0.9.

3.2.5 Artificial neural networks

Artificial neural networks (ANNs) are simulations of human brain working by computer programming [12]. ANNs have been applied in demand forecasting for travel [13] or using ANNs approach on automobile pricing model [14], heat transfer [15], or demand for electric load [16]. For more application area of ANNs, see [17-19]. The architecture of ANNs in this research is fully connected, feed-forward, and a multiple-layer perception neural network. It consists of three layers: an input layer, a hidden layer, and an output layer. Each of these layers contains neurons. In addition, the back propagation paradigm has become the most popular for demand forecasting. Figure 3 shows the topology of the neural network used in this research.

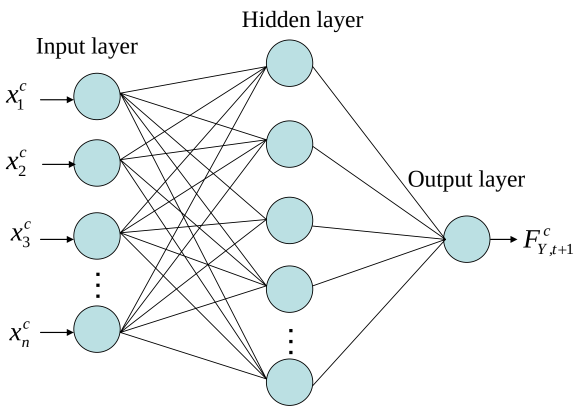

Figure 3: The topology of the neural network

The independent variables $x_1^c, \ldots, x_n^c$ are designed as input data for each country and $F_{Y,t+1}^c$ as demand forecasting for each country. All input data are inserted to each neuron at an input layer. The neurons at an input layer are connected to every hidden neuron and every hidden neuron is connected to the output neuron. Connections between neurons have numerical weights (w_{ji}) and these are adjusted in the training process. Each neuron has two main functions: the first function is the summation function. The second function is the activation function. The value for a neuron in the hidden or output layers is typically the sum of each incoming activation level times its respective connection weight. In Figure 3, each neuron in the hidden layer calculates the summation function (y_j) where j is the amount of neuron in hidden layer, $j = 1, 2, \ldots, 14$ and i is the amount of input data, $i = 1, 2, \ldots, 7$ by equation:

$$y_j = \sum_{i=1}^{n} x_i^c w_{ji} \tag{6}$$

After that, the result from summation is then modified by an activation function and becomes an output. This in turn becomes an input to one or more neurons. An activation function is a tansigmoid function (y_T) which transforms the input signals into output signals. It is represented by:

$$y_T = \frac{1 - e^{-y}}{1 + e^{-y}} \tag{7}$$

Finally, $F_{Y,t+1}^c$ in neuron of the output layer in Figure 3 is obtained by:

$$F_{Y,t+1}^c = \sum_{i=1}^{j} y_{Ti} w_i \tag{8}$$

Where w_i is a numerical weight which is connected between the neuron in the hidden layer with the neuron in the output layer. The ANNs modelling for demand forecasting of WPA is developed by using MATLAB. This computer programme is designed (around) the two stopping criteria for the training stage of ANNs for the selected country. The first criterion stopped the training process if the total number of iterations is 500,000. The second stopping criterion is based on the performance goal below or equal, and the training process is terminated [4]. A supervised feed-forward neural network learns from training data to discover patterns representing input and output variables. Usually, the process of learning involves the following stages.

1. Assign random numbers to the weights.
2. For every element in the training set (a set of sample observations used to develop the pattern or relationship among the observations), calculate

output using the summation functions embedded in the neurons.

3. Compare computed output with observed values.
4. Adjust the weights and repeat steps (2) and (3) if the result from step (3) is not less than a threshold value.
5. Repeat the above steps for other elements in the training set.

There are many input variables which are applied with an ANNs model. The input variables are collected through interviews from the Thailand Automotive Institute, Thai Autoparts Manufacturers Association, and automotive manufacturers. There are many input variables relative to the demand of WPA. After acquiring the input variables, they are tested for their correlation factor to the demand and then seven input variables remain for ANNs model. This research uses the input variables for forecasting model estimation during the period of 1997 to 2008.

Input variables for ANNs are:

1. Growth rate of export of each year in each country as %
2. Growth rate of import of each year in each country as %
3. Growth rate of GDP of each year in each country as %
4. Foreign exchange rate in each country as USD
5. Gross domestic expenditure *per capita* of each year in each country as USD
6. Average unit price for WPA of each year in each country as USD
7. Population of each year in each country

The numerical variables of seven variables can be seen in Tables A1-A5. The output neuron is the advanced demand of WPA. In this research, the data is divided into two series. There are the training series containing 42 data sequences and the testing series containing 8 data sequences which are the historical data in 8 years (1997-2004). The topology of ANNs in this research consists of seven inputs variables for the input layer, one hidden layer, and one neuron for the output layer. An ANNs model uses trial and error for deciding the number of neurons in the hidden layer by starting one neuron, up to fourteen neurons. The error goal is 0.005.

In addition, all models calculate MAE, MAPE, MSE, and RMSE values. After that, all forecasting models are compared with the forecasting errors.

3.3 *Measures of forecast accuracy*

There are several measurements in the forecasting. The general accuracy of forecasting is measured mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE). MAE is the easiest to understand and compute. The use of absolute values or squared values prevents positive and negative errors from offsetting each other. It measures the overall accuracy and provides an indication of the overall spread, where all errors are given equal weights. It cannot, however, be compared across series because it is scale dependent. MAPE is a relative measurement that corresponds to MAE ignoring the sign of the error term by adopting absolute changes and used for comparison across the testing data because it is scale independent [20]. In this research, accurate measurement of the five different forecasting models is based on MAPE. In general, the selected models are not very accurate in most of the measuring dimensions. The classified forecasts with MAPE values indicate that MAPE is less than 10% as highly accurate forecasting, between 10% and 20% as good forecasting, between 20% and 50% as reasonable, and forecasting larger than 50% as inaccurate forecasting [21].

Table 1: Comparisons of the forecasting models and accuracy measurements

	Naïve	Moving Average	Single Exponential Smoothing	Exponential Smoothing with Trend	ANNs
Japan		**(4 Years)**	**(alpha=0.9)**	**(alpha=0.9, beta=0.1)**	**(3,1,0.005)**
MAE	842.273	1,057.969	860.626	806.752	566.465
MAPE(%)	41.956	36.229	42.241	41.306	**15.212**
MSE	1,085,953.909	1,445,225.602	1,093,339.088	1,080,010.986	948,919.452
RMSE	1,042.091	1,202.175	1,045.629	1,039.236	974.125
China		**(2 Years)**	**(alpha=0.9)**	**(alpha=0.9, beta=0.9)**	**(14,1,0.005)**
MAE	1,463.000	2,021.450	1,539.875	1,304.738	6,607.430
MAPE(%)	34.566	43.271	35.933	**29.671**	50.310
MSE	4,633,574.455	8,721,185.575	5,148,171.258	4,051,082.000	45,246,337.230
RMSE	2,152.574	2,953.165	2,268.958	2,012.730	6,726.540
South Korea		**(2 Years)**	**(alpha=0.9)**	**(alpha=0.6, beta=0.9)**	**(9,1,0.005)**
MAE	426.545	386.300	419.234	449.709	37.845
MAPE(%)	1,141.622	598.135	1,203.298	1,106.337	498.202
MSE	334,052.909	274,482.250	334,691.304	366,792.000	1,556.334
RMSE	577.973	523.911	578.525	605.633	39.450
Germany		**(2 Years)**	**(alpha=0.6)**	**(alpha=0.3, beta=0.9)**	**(2,1,0.005)**
MAE	164.000	130.719	137.547	132.488	19.769
MAPE(%)	95.134	75.793	87.108	84.172	**9.774**
MSE	47,095.273	17,622.324	37,756.780	36,563.000	751.870
RMSE	217.014	132.749	194.311	191.214	27.420
Indonesia		**(2 Years)**	**(alpha=0.8)**	**(alpha=0.6, beta=0.3)**	**(5,1,0.005)**
MAE	445.000	501.571	425.733	388.313	457.967
MAPE(%)	51.977	49.772	36.058	47.751	**20.221**
MSE	353,480.250	498,593.786	266,336.882	326,085.394	433,021.897
RMSE	594.542	706.112	516.078	571.039	658.044

4 Results

Table 1 shows the results for each model. As the results, for each model is considered the accurate value. Accuracy measurement of the five models is based on MAPE. MAPE is a relative measurement used for comparison across the testing data because it is easy to interpret and is independent of scale. As illustrated in Table 1, moving average, single exponential smoothing and exponential smoothing with trend are able to achieve three reasonable forecasts (MAPE is between 20% and 50%) and two inaccurate forecasts (MAPE is larger than 50%) whereas naïve attains two reasonable forecasts (MAPE is between 20% and 50%) and three inaccurate forecasts (MAPE is larger than 50%). An ANNs model attains one highly accurate forecast (MAPE is less than 10%), one good forecast (MAPE is between 10% and 20%), one reasonable forecast (MAPE is between 20% and 50%), and two inaccurate forecasts (MAPE is larger than 50%). Therefore, an ANNs model is suitable for Japan (3 neurons for hidden layer, 1 neuron for output layer, error goal 0.005), Germany (2 neurons for hidden layer, 1 neuron for output layer, error goal 0.005), and Indonesia (5 neurons for hidden layer, 1 neuron for output layer, error goal 0.005) because MAPE is the lowest in these five models of each country. For China, the suitable model is an exponential smoothing with trend ($\alpha = 0.9, \beta = 0.9$). Lastly, there are no suitable models for South Korea because the five forecasting models give a higher error than 50%. The main reason is that the demand data of WPA of South Korea shows large fluctuations. South Korea encountered the domestic economic crisis. Within this section the automotive industry has decreased its production quantity. This reason results in lack of orders for the automotive parts, for both domestic and foreign markets. The Government of South Korea encourages the manufacturers of automotive parts to relocate their factories to other countries which have low labour costs and have a Free Trade Area (FTA) policy.

In addition, the results from the demand forecasting models substitute in linear programming model for calculating the optimal quantity for maximum profit of each country beneath objective function and constraints.

5 Application of linear programming model

Linear programming (LP) is a mathematic technique designed to use for planning and decisions. LP problems seek to maximize or minimize some quantity (usually profit or cost): this property is called the objective function of LP problems. The major objective is to maximize profits or minimize costs. The presence of restrictions or constraints is limited, which can affect objectivity. Nonetheless, there must be alternative courses of action from which to choose. The accurate forecasting model of each country gives a minimum error. The results from the accurate forecasting model are used for finding the optimal quantity for exporting to the five countries by using the LP model in order to receive maximum profit. The results from the LP model can be used for effective production planning or investment by informing manufacturers.

The optimal problem is composed of four parts such as form [22].

1. Objective function in the form of maximum or minimum: $f(X_1, X_2, \ldots, X_n)$
2. Constraint function
3. Decision variables in the equation and the limitation of the linear program. There are written by $X_1, X_2, \ldots, X_n$
4. Decision variables more than zero value

In 2008 the total production of WPA, as assessed from interviewing the Thai Autoparts Manufacturers Association, is about 58,800 tons. The demand of the domestic market is 34,800 tons and 24,000 tons for foreign markets. The forecasting results of the demand for the five countries are as follows: The forecasting result for Japan is 2,932.06 tons while the export limited condition is a minimum at 2,000 tons per annual. The forecasting result for China is 14,214.67 tons while the export limited condition is a minimum at 10,000 tons per annual. The forecasting result for South Korea is 44.25 tons while the export limited condition is a minimum at 10 tons per annual. The forecasting result for Germany is 223.06 tons while the export limited condition is a minimum at 200 tons per annual. The forecasting result for Indonesia is 2,174.60 tons while the export limited condition is a minimum at 500 tons per annual. The exported limited condition to other countries is a minimum at 4,000 tons per annual. The profit per ton of selling WPA, for domestic and foreign markets as seen from interviewing the Thai Autoparts Manufacturers Association, are as follows: 1) The profit per ton for Japan is 807.95 USD 2) The profit per ton for China is 369.54 USD 3) The profit per ton for South Korea is 425.77 USD 4) The profit per ton for Germany is 1603.72 USD 5) The profit per ton for Indonesia is 831.24 USD 6) The profit per ton for other countries is 415.25 USD and 7) The profit per ton for Thailand (domestic) is 302.20 USD. After that the result of forecasting demand, the profit per ton of selling WPA and the constraints are substituted in LP model. The LP model is constructed by using in the objective functions and constraints. Let

$X_1 =$ The optimal quantity for export to Japan (tons)

$X_2 =$ The optimal quantity for export to China (tons)

$X_3 =$ The optimal quantity for export to South Korea (tons)

$X_4 =$ The optimal quantity for export to Germany (tons)

$X_5 =$ The optimal quantity for export to Indonesia (tons)

$X_6 =$ The optimal quantity for export to other countries (tons)

$X_7 =$ The optimal quantity used in domestic (tons)

$$\begin{aligned} Max.profit, Z = {} & 807.95X_1 + 369.54X_2 + 425.77X_3 \\ & + 1603.72X_4 + 831.24X_5 + 415.25X_6 \\ & + 302.20X_7 \end{aligned} \tag{9}$$

Subject to the constraints

$$\begin{aligned} & X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 && \le 58{,}800 \\ & X_1 + X_2 + X_3 + X_4 + X_5 + X_6 && \le 24{,}000 \\ & X_1 && \le 2{,}932.06 \\ & X_2 && \le 14{,}214.67 \\ & X_3 && \le 44.25 \end{aligned}$$

X_4	≤ 223.06
X_5	$\leq 2{,}174.06$
X_6	$\geq 4{,}000$
X_7	$\leq 34{,}800$
X_1	$\geq 2{,}000$
X_2	$\geq 10{,}000$
X_3	≥ 10
X_4	≥ 200
X_5	≥ 500
$X_1, X_2, X_3, X_4, X_5, X_6, X_7$	≥ 0

Table 2 shows the results from the LP model which is the optimal quantity for exporting to each country and for receiving maximum profit. The results present export to Japan 2,932.06 tons, China 10,000 tons, South Korea 44.25 tons, Germany 223.06 tons, Indonesia 2,174.60 tons, other countries 8,626.03 tons, and Thailand (domestic) 34,800 tons, respectively. The result for maximum profit is 22,347,057.44 USD.Finally, these results are transformed to the Office of Industrial Economics, Thailand Automotive Institute, and Thai Autoparts Manufacturers Association. These offices provide help about the data to manufacturers. The manufacturers plan to export for maximum profit.

Table 2: The optimal quantity of each country for maximum profit in 2008

Country	Optimal quantity (tons)
Japan	2,932.06
China	10,000.00
South Korea	44.25
Germany	223.06
Indonesia	2,174.60
Other countries	8,626.03
Thailand (domestic)	34,800.00

6 Conclusions and recommendations

The objective of this research is to find the accurate forecasting model for predicting the advanced demand for WPA, and calculate the optimal quantity for exporting by using the LP model in order to receive maximum profit. The forecasting results are used for finding the optimal quantity for exporting to the five countries (Japan, China, South Korea, Germany, and Indonesia) by using the LP model. This research uses time series models and ANNs model. Time series models use the retrospective data of the WPA demand quantity to be input variables only, but ANNs model uses many input variables. The input variables influencing the demand of each year are as follows: growth rate of export in each country as %, growth rate of import in each country as %, growth rate of GDP in each country as %, foreign exchange rate in each country as USD, gross domestic expenditure *per capita* in each country as USD, average unit price for WPA, in each country as USD, and population in each country. This research has attempted to find the forecasting model for five countries by comparing the least errors. The reason is that these top five countries have a high demand for the number of WPA. These models are selected as naïve, moving average, single exponential smoothing, exponential smoothing with trend, and ANNs. The empirical results show that the ANNs model outperforms naïve, moving average, exponential smoothing, and exponential smoothing with trend. Considering the accurate values with MAPE, the demand forecasting with ANNs model is close to the actual demand for Japan, Germany, and Indonesia whereas an exponential smoothing with trend is close to the actual value for China. There is no suitable forecasting model for South Korea because the five forecasting models (naïve, moving average, single exponential smoothing, exponential smoothing with trend and ANNs) give a higher error (MAPE) than 50%, but it is possible to consider other forecasting models. The main reason is that the demand data for WPA of South Korea shows a pronounced fluctuation. The domestic economy is at a slowdown. In the section of the automotive industry production quantity is decreased and there is no investment. Within the automotive parts industry, neither domestic nor foreign markets are ordering, or for reasons of competition, the Government of South Korea encourages the manufacturers of automotive parts to relocate their factories to other countries which have low labour costs and have a Free Trade

Area (FTA) policy. The MAPE values calculated for the five countries are compared with criteria according to [20], with which MAPE has greater errors than 50% as inaccurate forecasting. Japan,

Germany, and Indonesia receive ANNs model. China receives an exponential smoothing with trend model. There is no forecasting model for South Korea. Table 3 shows the forecasting models for the five countries.

Table 3: The forecasting models for the five countries

Country	Model	MAPE(%)
Japan	ANNs (3,1,0.005)	15.212
China	Exponential smoothing with trend (α=0.9,β=0.9)	29.671
South Korea	NA	NA
Germany	ANNs (2,1,0.005)	9.774
Indonesia	ANNs (5,1,0.005)	20.221

The input variables influencing forecasting have many, and there are numerous important input variables for ANNs model. There are abundant variables which influence forecasting, including important input variables for the ANNs model. ANNs model has a large number of parameters, and is suitable for forecasting, giving the fewest errors. This complies with [3-5] the type of forecasting which uses ANNs. After that the results of demand forecasting are used for calculating to find the maximum profit for exporting by the LP model. The output from the LP model decides which countries receive the WPA first. The contribution of this research is in finding forecasting models for the WPA. The results are used by the Thailand Automotive Institute or the Thai Autoparts Manufacturers Association to help the manufacturers to prepare the production planning or market share. Moreover, the manufacturers use this information when considering increasing or decreasing investment. The automotive parts industry is particularly important to Thailand. The Thai Government promotes it as the principal industry in Thailand. It brings foreign money and employment into the country. The need for accurate demand forecasting of automotive parts is particularly important because of the industry's significant contribution to the economy. To a large extent, manufacturers rely on forecasting results for future production planning For future study, the forecasting is a complex of data and there are many forecasting models which use the long term for finding the suitable model and maximum profit by the LP model. The computer programme is designed to calculate the forecasting value and the optimal quantity based on the maximum profit for each country. This computer programme is available to forecast the various forecasting models. In addition, this computer programme can be applied to various products such as agricultural yield or industrial products. This research also extends to forecast other automotive parts

Acknowledgements

This research is supported by Rajamangala University of Technology Phra Nakhon. In addition,

this research is supported by the data from the Customs Department, Thailand Automotive Institute, The Office of Industrial Economics, Department of Export Promotion, and Thai Autoparts Manufacturers Association.

Appendix A

Tables A1-A5 are provided in this appendix.

Table A1: An overview of inputs data for an ANNs model of Japan

Year	Export (%)	Import (%)	Growth Rate of GDP (%)	Foreign Exchange Rate (JPY/US$)	Gross Domestic Expenditure Per Capita in Japan (US$)	Average Unit Prices Wheel Including Parts and Accessories for Motor Vehicles (US$/Ton)	Population	Demand Wheel Including Parts and Accessories for Motor Vehicles (Tons)
1997	11.11	0.51	1.57	121.05	33,758.00	3,239.56	126,150,187	821
1998	-2.71	-6.84	-2.05	130.88	30,494.05	4,859.25	126,468,939	411
1999	1.89	3.61	-0.14	113.81	34,463.12	2,389.04	126,765,489	1,853
2000	12.70	9.19	2.86	107.86	36,741.71	2,637.81	127,034,058	2,463
2001	-6.93	0.63	0.18	121.56	32,178.65	2,659.82	127,273,272	2,584
2002	7.51	0.92	0.26	125.22	30,736.18	1,942.97	127,482,808	2,646
2003	9.21	3.89	1.41	115.98	33,128.06	2,322.79	127,659,077	3,341
2004	13.93	8.12	2.74	108.18	36,040.75	3,199.17	127,798,083	3,098
2005	6.96	5.81	1.93	110.12	35,592.71	4,547.80	127,896,740	1,628
2006	9.67	4.22	2.04	116.33	34,199.99	4,164.21	127,953,099	2,644
2007	8.43	1.52	2.39	117.81	34,224.71	4,635.16	127,966,710	3,499
2008	1.76	0.90	0.44	103.47	38,577.83	4,039.75	127,293,092	5,128

Table A2: An overview of inputs data for an ANNs model of China

Year	Export (%)	Import (%)	Growth Rate of GDP (%)	Foreign Exchange Rate (CNY/US$)	Gross Domestic Expenditure Per Capita in China (US$)	Average Unit Prices Wheel Including Parts and Accessories for Motor Vehicles (US$/Ton)	Population	Demand Wheel Including Parts and Accessories for Motor Vehicles (Tons)
1997	30.76	10.16	9.30	8.29	810.28	6,664.20	1,215,688,291	118
1998	5.70	0.30	7.80	8.28	851.89	5,964.86	1,226,923,557	98
1999	9.08	11.38	7.60	8.28	887.84	4,184.68	1,237,648,051	110
2000	31.11	34.61	8.40	8.28	956.04	2,409.86	1,247,685,039	200
2001	11.37	14.24	8.31	8.28	1,047.31	2,774.71	1,257,079,958	280
2002	19.72	21.19	9.10	8.29	1,148.64	1,870.01	1,265,880,056	653
2003	16.62	19.69	10.00	8.29	1,293.26	972.66	1,274,233,866	2,693
2004	21.98	23.80	10.10	8.29	1,510.19	1,049.29	1,282,294,203	5,587
2005	21.74	17.56	10.40	8.20	1,784.76	1,587.22	1,290,208,472	6,441
2006	18.65	16.07	11.61	7.98	2,136.98	1,547.94	1,298,014,226	11,488
2007	15.69	12.90	13.01	7.62	2,604.21	1,477.55	1,305,713,911	14,575
2008	9.58	7.08	9.05	6.96	3,292.12	1,847.71	1,314,357,176	12,979

Table A3: An overview of inputs data for an ANNs model of South Korea

Year	Export (%)	Import (%)	Growth Rate of GDP (%)	Foreign Exchange Rate (KRW/US$)	Gross Domestic Expenditure Per Capita in South Korea (US$)	Average Unit Prices Wheel Including Parts and Accessories for Motor Vehicles (US$/Ton)	Population	Demand Wheel Including Parts and Accessories for Motor Vehicles (Tons)
1997	21.63	3.46	4.65	954.00	11,275.97	1,294.34	45,786,154	1,355
1998	12.65	-21.81	-6.85	1,402.11	7,485.63	605.51	46,146,197	14
1999	14.62	27.80	9.49	1,190.13	9,582.86	820.44	46,478,875	489
2000	19.14	20.06	8.49	1,131.16	10,937.50	1,083.42	46,780,246	1,427
2001	-3.43	-4.86	3.97	1,291.50	10,242.78	731.51	47,047,215	1,222
2002	12.10	14.43	7.15	1,249.79	11,567.61	855.90	47,281,557	1,477
2003	14.48	11.08	2.80	1,194.54	12,805.66	856.04	47,490,388	1,124
2004	19.74	11.74	4.62	1,150.91	14,270.87	1,418.83	47,683,978	477
2005	7.77	7.59	3.96	1,027.59	16,532.94	1,223.32	47,869,837	171
2006	11.37	11.29	5.18	969.90	18,481.07	1,216.67	48,050,441	7
2007	12.61	11.68	5.11	935.27	19,840.55	2,201.48	48,223,854	11
2008	5.73	3.66	2.22	1,102.84	19,295.52	2,128.84	48,152,294	7

Table A4: An overview of inputs data for an ANNs model of Germany

Year	Export (%)	Import (%)	Growth Rate of GDP (%)	Foreign Exchange Rate (EUR/US$)	Gross Domestic Expenditure Per Capita in Germany (US$)	Average Unit Prices Wheel Including Parts and Accessories for Motor Vehicles (US$/Ton)	Population	Demand Wheel Including Parts and Accessories for Motor Vehicles (Tons)
1997	11.71	8.22	1.80	0.88	26,325.93	8,975.99	82,070,023	165
1998	7.96	9.45	2.03	0.9	26,586.54	11,042.45	82,164,693	28
1999	5.94	8.55	2.01	0.94	26,066.33	7,696.18	82,234,660	73
2000	13.53	10.17	3.21	1.08	23,086.47	5,302.14	82,308,801	561
2001	6.44	1.23	1.24	1.11	22,949.73	5,898.94	82,395,462	247
2002	4.29	-1.44	0.00	0.54	24,453.02	6,420.18	82,485,207	560
2003	2.46	5.36	-0.22	0.88	29,577.03	5,127.08	82,568,070	453
2004	10.25	7.28	1.21	0.81	33,228.46	5,411.30	82,627,591	350
2005	7.67	6.53	0.77	0.8	33,772.47	6,742.56	82,652,369	161
2006	12.69	11.85	2.96	0.8	35,250.86	6,836.95	82,640,853	143
2007	7.47	5.03	2.46	0.73	40,162.21	6,233.92	82,599,470	202
2008	2.68	4.21	1.27	0.68	44,362.75	8,018.61	82,264,266	233

Table A5: An overview of inputs data for an ANNs model of Indonesia

Year	Export (%)	Import (%)	Growth Rate of GDP (%)	Foreign Exchange Rate (IDR/US$)	Gross Domestic Expenditure Per Capita in Indonesia (US$)	Average Unit Prices Wheel Including Parts and Accessories for Motor Vehicles (US$/Ton)	Population	Demand Wheel Including Parts and Accessories for Motor Vehicles (Tons)
1997	8.05	14.13	4.70	2,903.54	1,162.24	0.00	203,954,036	0
1998	11.59	-6.04	-13.13	10,285.38	507.12	4,500.06	206,786,073	8
1999	-31.78	-39.44	0.79	7,876.90	736.59	7,321.19	208,825,347	12
2000	26.79	22.09	4.92	8,415.79	779.53	10,136.84	211,692,873	0
2001	0.64	4.18	3.64	10,293.78	747.74	0.00	214,574,762	0
2002	-1.22	-4.25	4.50	9,350.14	899.73	10,650.35	217,465,933	59
2003	5.89	1.56	4.78	8,592.80	1,065.43	3,040.24	220,354,725	343
2004	13.53	26.65	5.03	8,945.82	1,150.57	2,918.26	223,224,904	1,330
2005	16.60	17.77	5.69	9,721.65	1,264.55	3,754.61	226,063,044	840
2006	9.41	8.58	5.51	9,183.77	1,593.08	4,543.92	228,864,475	1,314
2007	8.02	8.89	6.32	9,183.50	1,868.60	3,819.20	231,626,979	2,446
2008	10.02	10.11	6.01	9,684.89	2,246.71	4,156.18	227,345,082	2,304

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