Thailand's Para Rubber Production Forecasting Comparison

Onuma Kosanan and Nantachai Kantanantha

Abstract—**The objective of this research is to construct a Thailand's Para rubber production forecasting model. Three forecasting techniques used in this research are auto regressive integrated moving average (ARIMA), artificial neural network (ANN) and support vector machine (SVM). The mean absolute percentage error is used to identify the most appropriate model. The results of the research show that the artificial neural network model obtains the lowest mean absolute percentage error of 0.0037%, while the auto regressive integrated moving average and support vector machine have mean absolute percentage error of 0.0419% and 0.0434%, respectively.**

Index Terms—**forecasting, Para rubber, auto regressive integrated moving average, artificial neural network, support vector machine**

I. Introduction

Forecasting is useful for providing an aid to decision making and in planning the future. For Thailand, which is an agricultural country, forecasting the agricultural production is extremely important since it benefits all parties involved in this business. The Office of Agricultural Economics of Thailand [1] releases yearly reports for all common agricultural products in each province of Thailand such as Para rubber, rice, sugar cane, and pineapples. In 2012, total export value of Thailand was 7,091,162 million baht, increased from last year 383,311 million baht or increased by 5.71 percent. For agricultural products, the export value decreased from 1,447,716 million baht in 2011 to 1,349,335 million baht in 2012, or decreased by 6.80 percent.

Major Thailand's agricultural product exports for year 2012 were natural rubber, rice and products, and sugar and products as shown in Table 1. It can be seen that rubber (Fig. 1.) is the number one in the agricultural export value of Thailand. Table 2 shows Para rubber data: area, production, yield, farm price and farm value during 2003-2013. Important export markets of Para rubber are China, Japan, United States of America, Malaysia, Indonesia, South Korea, United Kingdom, Vietnam, Cambodia and Australia, respectively.

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This research focuses on the development of Para rubber production forecasting model by comparing between auto regressive integrated moving average (ARIMA), artificial neural network (ANN) and support vector machine (SVM).

The structure of this paper is organized as follows. Section II reviews the relevant literature. The data and accuracy measurement are presented in Section III. In Section IV, the models are developed and the results of three methods are compared. Finally, the conclusions are drawn in Section V.

TABLE I
EXPORT VALUE OF MAJOR AGRICULTURAL PRODUCTS, 2010-2012
Value: Million Baht

Item	2010	2011	2012
Total export value	6,176,170	6,707,851	7,091,162
Value of agricultural products	1,135,750	1,447,716	1,349,335
Top ten of major agricultural products			
Natural rubber	296,380	440,890	336,304
Rice and products	180,727	210,527	158,434
Sugar and products	76,327	116,949	132,137
Fishes and products	99,039	112,150	131,562
Shrimps and products	101,141	110,643	96,630
Fruits and products	63,072	81,513	84,374
Cassava and products from cassava	66,889	77,689	84,322
Product from chicken meat	52,223	60,293	67,849
Vegetables and products	19,238	21,425	21,035
Residues and waste, prepared animal fodder	18,023	19,582	16,772
Other agricultural products	162,691	196,055	219,916

Source: Centre for Agricultural Information, Office of Agricultural Economics, Thailand, http://www.oae.go.th

TABLE II
PARA RUBBER: AREA, PRODUCTION, YIELD, FARM PRICE AND FARM VALUE, 2003-2013

Year	Planted area (1,000 rais)	Harvested area (1,000 rais)	Production (1,000 tons)	Yield per rai (Kgs.)	Farm price (Baht per kg.)	Farm value (Million baht)
2003	12,619	10,004	2,860	286	37.76	107,994
2004	12,954	10,350	3,007	291	44.13	132,699
2005	13,609	10,569	2,980	282	53.57	159,639
2006	14,355	10,893	3,071	282	66.24	203,423
2007	15,362	11,043	3,022	274	68.90	208,216
2008	16,717	11,372	3,167	278	73.66	233,281
2009	17,254	11,600	3,090	266	58.47	180,689
2010	18,095	12,058	3,052	253	103.00	314,333
2011	18,761	12,766	3,349	262	124.00	415,263
2012	19,273	13,807	3,625	263	87.15	315,944
2013(p)	20,334	15,130	3,863	255	75.09	290,072

Source: Food and Agriculture Organization of the United Nations
Updated by Office of Agricultural Economics, Thailand
Remark: Data as of January, 2013
(p): Preliminary Data

Fig. 1. Para rubber production in Thailand

II. Literature Review

A. Auto Regressive Integrated Moving Average

Auto regressive integrated moving average (ARIMA) model established by Box and Jenkins [2] has been widely used for the purpose of time series forecasting. An ARIMA model is linearly combined by several previous points random errors, and the forecast is a function of the past observations and the errors. The conventional ARMA(p,q) formulation described as

$$y_t = \delta + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where δ is a constant term, ϕ_i is the ith autoregressive coefficient, θ_j is the jth moving average coefficient, ε_t is the error term at time t, ε_{t-j} is the random error of a prior point at time $t-j$, p and q are the orders of autoregressive and moving average terms, respectively. If the time series data is not stationary, it should be differenced to become stationary. This results in an "integrated" ARMA (i.e. ARIMA) model, denoted by ARIMA(p,d,q), where d is the order of differencing. Building an ARIMA model includes three major steps: model identification, parameter estimation, and diagnostic checking. In model identification process, one or more model candidates could be found suitable for the time series. In such case, autocorrelation function (ACF) and partial autocorrelation function (PACF) can be applied to make the first guess about the orders of the ARIMA model. However, if the models show both autoregressive and moving average nature, such method cannot identify the orders since both ACF and PACF will show exponential decay and damped sinusoid. In this case, other criteria should be adopted to determine the order of the ARIMA model. The typical criteria are Akaike's information criterion (AIC) and Bayesian information criterion (BIC). Once the model is identified, the parameters need to be estimated, and in principle the selected parameters should generate the lowest residual. This can be accomplished by using the Yule–Walker Estimation or Maximum Likelihood Estimation. A common method is to test the randomness of the residuals using Ljung–Box Statistics, and non-significant P-values indicate that the residuals are uncorrelated and the proposed model is suitable for fitting the historical data.

B. Artificial Neural Network

Artificial neural network (ANN) is a computer programming that mimic human nervous system. It can be used to model relationship between given inputs and their related outputs from examples; this learning process is similar to human learning system. ANN is made up of simple processing elements called neurons connected together. The neurons can be located in the input layer, hidden layer and output layer as shown in Fig. 2. ANN is used to model or 'learn' relationship by tuning a set of parameters called 'weight' (the strength of the connection between neurons). This weight alteration process is called training. In the training process, a set of examples of input-output pairs is passed through the model and the weights adjust in order to minimize the error between the answer from the network and the desired output. The weight adjustment procedure is controlled by the learning algorithm. Once the error is minimal, the network is successfully trained. The trained network is able to predict output for unseen input.

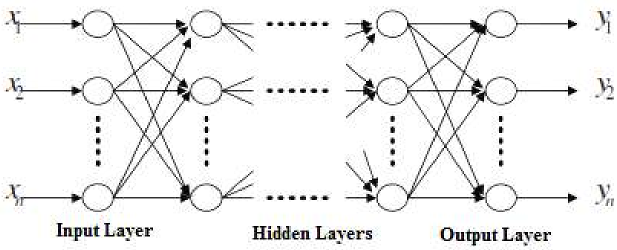

Fig. 2. The multi-layer feed-forward neural network [3]

The back propagation (BP) algorithm is the most extensively adopted learning [4]. BP is the algorithm used in this study. The algorithm can be summarized as follows [5].

1. Forward pass

Feed input through the network to attain output by calculate weighted sum (S_j) for every neuron.

$$S_j = \sum_i a_i w_{ij} \tag{2}$$

where a_i is the activation level of unit i, and w_{ij} is the weight from unit i to unit j (unit i is in one layer before unit j).

Transfer function, applied to the output in this research, is sigmoid transfer function. The equation for the sigmoid function is as follows.

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

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The result becomes the output of unit j. The same procedure repeats for all neurons.

2. Backward pass

Calculate error δ and weight changes for all neurons as follows.

For the output layer, $\delta_j = \left(t_j - a_j\right) f'\left(S_j\right)$ (4)

For the hidden layer, $\delta_j = \left[\sum_k \delta_k w_{kj}\right] f'\left(S_j\right)$ (5)

where t_j is the target value for unit j, a_j is the output value for unit j, $f'(x)$ is the derivative of the sigmoid function f, S_j is weighted sum of inputs to j, weight adjustment is calculated as $\Delta w_{ji} = \eta \delta_j a_i$ where η is the learning rate.

These processes of forward and backward pass repeat with new input vector until stopping criteria are met.

The multi-layer perceptron (MLP) learning with back propagation is the most widely used type of ANN reported in literature. According to [6], the advantage of using ANN in forecasting is that ANN is suitable to model system where rules for governing the system behavior are not very well understood.

There have been reported comparing ANN with traditional forecasting techniques. For example, [7] compared the accuracy of ARIMA, regression and ANN to forecast aggregate retail sales. The results suggested that the nonlinear method is the preferred approach to model retail sales. The overall best model for retail sales forecasting is the ANN model with deseasonalized time series data. The results agreed well with [8] which employed exponential smoothing, ARIMA and ANN to forecast Thailand's rice export. The results suggested that Holt-Winters and Box-Jenkins models provided satisfactory result with seen data, but did not perform well with unseen data, while ANN produced better predictive accuracy. Similar result was also reported by [9] in which ARIMA, ANN, and combined methods were compared in forecasting Chinese food grain price. The results suggested that ANN outperformed other techniques.

There have also been reported combining ANN with traditional forecasting techniques. For example, [10] integrated ARIMA with ANN in order to take advantage from both linear and nonlinear modeling and found that this integrated technique provided better forecasting accuracy. Reference [11] obtained the similar result. In their study, the hybrid forecasting model between ANN and ARIMA was developed to forecast the number of monthly tourist arrivals to Turkey. The results indicated that the hybrid model had a better performance.

C. Support Vector Machine

Support vector machine (SVM) is a type of function approximator based on the structured risk minimization principle. Recently, SVM has become more interested by researchers and has been increasingly applied in forecasting. For example, [12] used SVM to forecast production values of machinery industry. They also used the seasonal time series autoregressive integrated moving average (SARIMA) model and general regression neural network (GRNN). The results showed that SVM outperformed other techniques. Similar result was reported by [13], where advanced machine learning techniques, including neural network, recurrent neural network, and support vector machine, were used to forecast demand of simulated supply chain in comparison with more traditional techniques including naïve forecasting, trend, moving average, and linear regression. The results suggested that recurrent neural network and support vector machine delivered better forecasting accuracy but the results were not statistically significantly better than that of the regression model.

Instead of comparing SVM against traditional forecasting technique, some researchers took different approach by combining the two together. For example, [14] suggested a hybrid model of ARIMA and SVM. A case study is to forecast Hebei province daily load power data. The results showed that the hybrid model can effectively improve the forecasting accuracy.

SVM uses linear model to implement nonlinear class boundaries through some nonlinear mapping the input vectors x into the high-dimensional feature space [15]. A linear model constructed in the new space can represent a nonlinear decision boundary in the original space. In the new space, an optimal separating hyperplane is constructed. Thus, SVM is known as the algorithm that finds a special kind of linear model, *the maximum margin hyperplane*. The maximum margin hyperplane gives the maximum separation between the decision classes. The training examples that are closest to the maximum margin hyperplane are called *support vectors*. All other training examples are irrelevant for defining the binary class boundaries.

For the linearly separable case, a hyperplane separating the binary decision classes in the three-attribute case can be represented as the following equation:

$$y = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 \quad (6)$$

where y is the outcome, x_i are the attribute values, and there are four weights w_i to be learned by the learning algorithm. In (6), the weights w_i are parameters that determine the hyperplane. The maximum margin hyperplane can be represented as the following equation in terms of the support vectors:

$$y = b + \sum \alpha_i y_i x(i) \cdot x \quad (7)$$

where y_i is the class value of training example $x(i)$ and $\cdot$ represents the dot product. The vector x represents a test example and the vectors $x(i)$ are the support vectors. In this equation, b and α_i are parameters that determine the hyperplane. From the implementation point of view, finding the support vectors and determining the parameters b and α_i are equivalent to solving a linearly constrained quadratic programming (QP).

As mentioned above, SVM constructs linear model to implement nonlinear class boundaries through the transforming the inputs into the high-dimensional feature space. For the nonlinearly separable case, a high-dimensional version of (7) is simply represented as follows.

$$y = b + \sum \alpha_i y_i K\left(x(i), x\right). \tag{8}$$

The function $K\left(x(i), x\right)$ is defined as the kernel function. There are some different kernels for generating the inner products to construct machines with different types of nonlinear decision surfaces in the input space. Choosing among different kernels the model that minimizes the estimate, one chooses the best model. Common examples of the kernel function are the polynomial kernel $K(x,y) = (xy+1)^d$ and the Gaussian radial basis function $K(x,y) = \exp\left(-1/\delta^2 (x-y)^2\right)$ where d is the degree of the polynomial kernel and δ^2 is the bandwidth of the Gaussian radial basis function kernel.

For the separable case, there is a lower bound 0 on the coefficient α_i in (8). For the non-separable case, SVM can be generalized by placing an upper bound C on the coefficient α_i in addition to the lower bound [16]. The analysis procedure applied in this study is illustrated in Fig. 3.

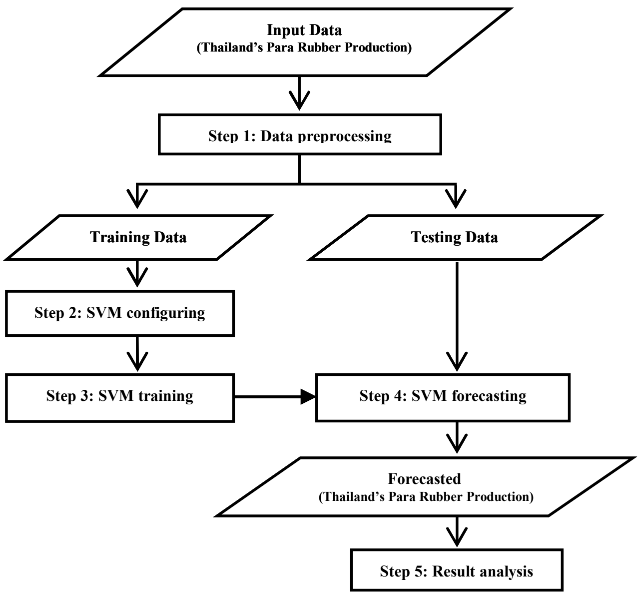

Fig. 3. Procedure of SVM tuning [17].

III. Application

A. Data

The data used in this study are Para rubber production in Thailand between 1990 and 2013 as shown in Table 3. The data are divided into two parts. The first 18 years are for model fitting and the last 6 years are for model testing.

B. Forecasting performance evaluation

Both mean absolute error (MAE) and mean absolute percentage error (MAPE) are used as the measures of forecasting accuracy. The formulations of these measures are defined as [18]:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|p_t^{true} - p_t^{forecast}\right|, \tag{9}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{p_t^{true} - p_t^{forecast}}{p_t^{true}}\right| \times 100\% \tag{10}$$

where N is the number of forecasting periods, p^{true} is the actual observation value for a time period t and $p^{forecast}$ is the forecast value for the same period. The MAE reveals the average variation between the forecasts and true values while the MAPE, as unit-free measure, has good sensitivity for small changes in data, does not display data asymmetry and has very low outlier protection.

TABLE III
Para rubber production in Thailand between 1990 and 2013

Year	Planted area (Rais)	Harvested area (rais)	Yield per rai (Kgs.)	Actual Data Production (tons)
1990	8,181,825	6,520,494	162	1,058,183
1991	8,600,617	6,861,470	169	1,162,242
1992	8,920,736	7,205,458	192	1,380,988
1993	9,279,829	7,571,124	199	1,505,832
1994	9,630,300	7,809,177	209	1,629,512
1995	9,921,084	7,977,245	212	1,693,078
1996	10,142,523	8,190,023	220	1,802,338
1997	10,544,840	8,403,162	225	1,890,072
1998	11,024,346	8,665,068	224	1,943,124
1999	11,457,921	8,950,522	229	2,048,156
2000	11,650,733	9,137,973	249	2,278,653
2001	12,144,471	9,399,647	268	2,522,508
2002	12,429,594	9,711,027	271	2,633,124
2003	12,619,350	10,004,112	286	2,860,093
2004	12,953,573	10,349,941	291	3,006,720
2005	13,608,757	10,569,366	282	2,979,722
2006	14,355,378	10,893,098	282	3,070,520
2007	15,362,346	11,042,811	274	3,022,324
2008	16,716,945	11,371,889	278	3,166,910
2009	17,254,317	11,600,447	266	3,090,280
2010	18,095,028	12,058,237	253	3,051,781
2011	18,461,231	12,765,636	262	3,348,897
2012	19,273,000	13,806,821	263	3,625,295
2013(p)	20,334,000	15,130,363	255	3,862,996

Source: Food and Agriculture Organization of the United Nations
Updated by Office of Agricultural Economics, Thailand
Remark: Data as of January, 2013
(p): Preliminary Data

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IV. Results And Discussion

The comparisons of forecasting models for the Para rubber production are made between ARIMA(0,1,0), ANN and SVM models. The forecasting results of those models are presented in Table 4 and the forecasting performances are shown in Table 5. Through model comparisons, the ANN model performs the best. As seen from Table 5 and Fig. 4-9, it is clear that the ANN model performs much better than ARIMA(0,1,0) model and SVM model. The MAPE is used to identify the most appropriate model. The results of the research shows that the ANN model has the lowest MAPE of 0.0037%, while ARIMA(0,1,0) and SVM models have MAPE of 0.0419% and 0.0434%, respectively. However, the forecasts from these models are not statistically significant difference according to the Tukey simultaneous tests as shown in Table 6.

TABLE IV
COMPARISON OF PARA RUBBER PRODUCTION FORECASTS FROM THREE FORECASTING MODELS, 2008-2013

Year	Actual Data Production (tons):	Production Forecasting (tons)		
		ARIMA (0,1,0)	ANN	SVM
2008	3,166,910	3,137,862	3,180,777	2,977,756
2009	3,090,280	3,253,399	3,090,634	3,315,124
2010	3,051,781	3,368,937	3,052,783	3,017,278
2011	3,348,897	3,484,475	3,338,297	3,016,910
2012	3,625,295	3,600,013	3,659,116	3,649,641
2013	3,862,996	3,715,550	3,882,996	3,905,321

TABLE V
FORECASTING PERFORMANCE EVALUATION

Forecasting Model	Forecasting Performance Evaluation	
	MAE (Tons)	MAPE (%)
ARIMA(0,1,0)	136,271.65	0.0419
ANN	13,274.06	0.0037
SVM	141,193.17	0.0434

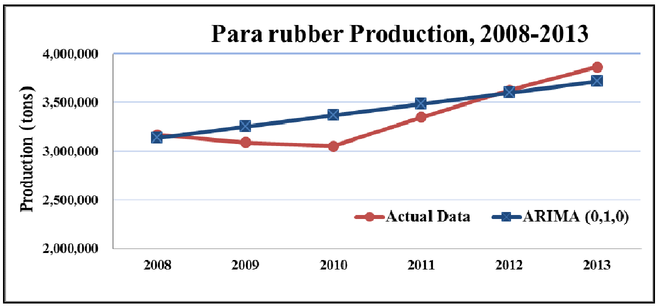

Fig. 4. Comparison of actual and forecast values from ARIMA(0,1,0) model for testing data, 2008-2013

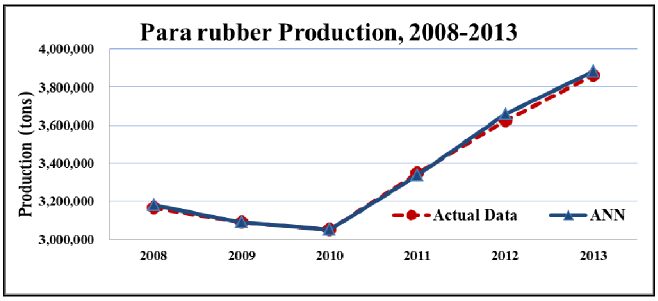

Fig. 5. Comparison of actual and forecast values from ANN model for testing data, 2008-2013

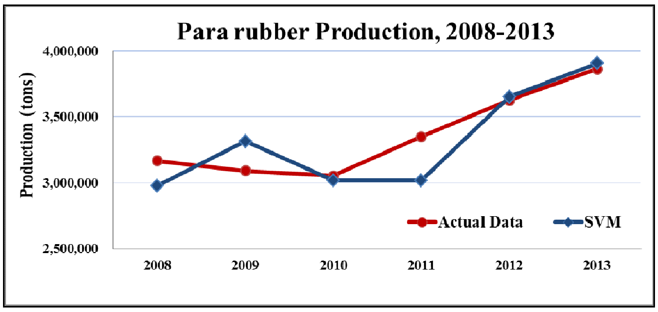

Fig. 6. Comparison of actual and forecast values from SVM model for testing data, 2008-2013

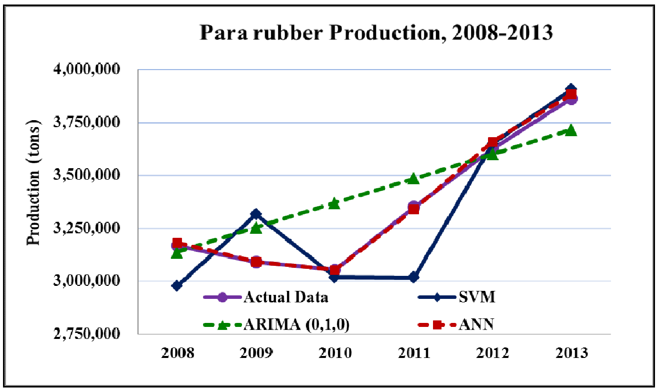

Fig. 7. Comparison of actual and forecast values from all models for testing data, 2008-2013

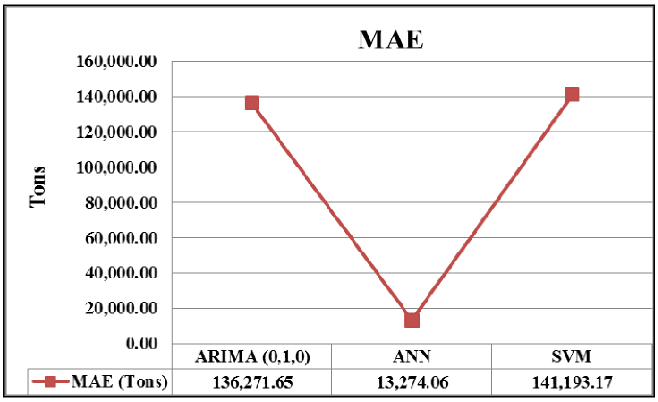

Fig. 8. Comparison of forecasting performance evaluation; MAE

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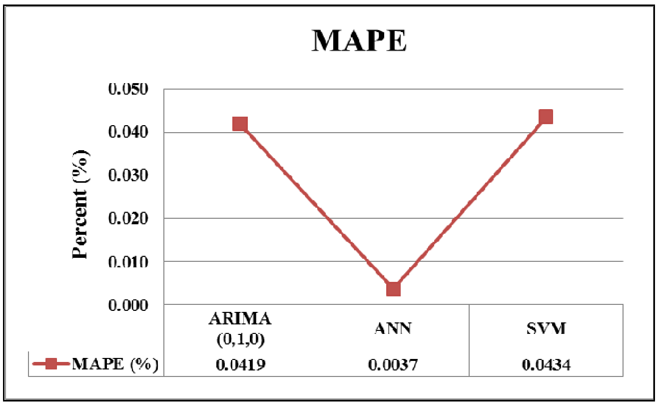

Fig. 9. Comparison of forecasting performance evaluation; MAPE

TABLE VI
TUKEY SIMULTANEOUS TESTS

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Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of Method

Individual confidence level = 98.89%

Method = Actual subtracted from:

Method           Lower   Center  Upper  --------+---------+---------+---------+-
ARIMA (0,1,0)  -451843   69013  589869      (--------------*--------------)
ANN            -511115    9741  530597     (--------------*--------------)
SVM            -564877  -44022  476834   (--------------*--------------)
                                        --------+---------+---------+---------+-
                                     -350000         0    350000    700000

Method = ARIMA(0,1,0) subtracted from:

Method         Lower    Center   Upper  --------+---------+---------+---------+-
ANN          -580128   -59272  461584  (--------------*--------------)
SVM          -633890  -113034  407822  (--------------*--------------)
                                        --------+---------+---------+---------+-
                                       -350000         0    350000    700000

Method = MLP subtracted from:

Method         Lower   Center   Upper  --------+---------+---------+---------+-
SVM          -574618  -53762  467094   (-------------*--------------)
                                       --------+---------+---------+---------+-
                                      -350000         0    350000    700000
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V. CONCLUSIONS

This research examines the application of two computational intelligence techniques namely artificial neural network (ANN) and support vector machine (SVM) in Thailand's Para rubber production forecasting in comparison with auto regressive integrated moving average (ARIMA).

The ANN model provides better accuracy than ARIMA and SVM models because it is a non-linear mapping between input and output. However, when the results of forecasting are tested by Tukey Simultaneous tests, the results show that the forecasts of the three models are not statistically significant difference. Furthermore, ANN has no statistical assumption about the data distribution, hence made it more versatile. Nevertheless, ANN suffers from overtraining problem and also another major drawback of ANN is its black-box like ability. SVM has recently been compared with ANN as it solve overtraining problem of ANN.

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