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The Combination of Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machines (SVM) for Daily Rubber Price Forecasting

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Abstract. Natural rubber (NR) price is easily affected by the long term and short term exchange rate of developments on supply and demand sides, as well as the effects of exchange rates. Due to the fact that monthly, quarterly, and annually data have undergone the smoothing technique, it may have missed out some of the important characteristics or information describing the rubber price. Since the NR price is changing daily, therefore, this study focuses on predicting the future daily prices. A combination model of Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machine (SVM) is proposed in order to capture the future value of NR prices. The experimental results show that the proposed model performs the best whereby it has under-predicted by 6.31% with the r value of 0.9976 compared to single ARIMA and SVM models. As the results, the combination model shows to be an effective tool in improving the forecasting accuracy by reducing the model forecast error.

1. Introduction

According to Burger [1], the natural rubber (NR) prices will be affected by the long term and short term exchange rate of developments on the supply side or on the demand side. Besides that, the quarterly and annually data would not be possible to trace a large part of the effects of exchange rates. Furthermore, the variables that influenced the price of NR and the production and consumption are highly inaccurate [1]. Due to the fact that monthly, quarterly, and annually data have undergone the smoothing technique, it may have missed out some of the important characteristics or information



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describing the rubber price. Therefore, questions have been raised about the accuracies of monthly, quarterly and annually data used for NR price forecasting. Based on the rubber price market, the NR price is changing daily which it operates on daily basis. Hence, the daily rubber price data is using in this research to forecast the future daily NR price.

One of the traditional forecasting method used in various areas is ARIMA model. ARIMA has been used in predicting crude palm oil prices [2], natural rubber export [3-4], agricultural productivity [5-7], day-ahead electricity price [8] and others. However, ARIMA technique model only linear and stationary process which would be a limitation in case of non-linear and non-stationary time series data [9].

On the other hand, Support Vector Machines (SVM) is the nonlinearity model with the properties of minimization of the empirical risk, upper bound on the generalization error [10] and the structural risk [11]. SVM categories into classification and regression. The nonlinear Support Vector Regression (SVR) is applying to forecast the daily rubber price because SVM able to capture the nonlinearity and nonstationarity better than ARIMA model [12].

However, SVM is lacking of transparency. Its dimension may be very high and cannot shows a simple parametric which are not constant [13]. Therefore, hybrid method has been thought of as an important key in improving the forecasting accuracy. In the history of development forecasting method, hybrid model which combines two or more forecast methods is used to improve the accuracy and reduces the errors [14]. According to Armstrong [15], hybrid forecast method is very useful when there are uncertainty on selecting the most accurate forecast method, uncertainty of forecasting situation, and large forecast errors with high expenses.

2. Hybrid model in forecasting

2.1. Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is a subset which specific for univariate modelling. The time series of ARIMA expressed in past values term with autoregressive component and the moving average component [16] which values of 'white noise' error term. According to Box [17], the future value of variable was expected to linear function to three linear components: Autoregression (AR), Integration (I), and Moving Average (MA) method in an ARIMA model. The ARIMA method represented as follows:

$$\phi_p(B)\nabla^d Y_t = \theta_q(B)e_t \quad (1)$$

$$\left(1 - \sum_{i=1}^p \phi_i B^i\right)(1-B)^d y_t = \left(1 - \sum_{i=1}^q \theta_i B^i\right)e_t \quad (2)$$

where y_t is t^{th} observation in series data, ϕ is parameter of AR (p) model, and θ is parameter of MA(q) model.

There are three fundamental steps of building up an ARIMA model: model identification, parameter estimation, and diagnostic checking with analysis of time series and forecasting applications [17]. A time series is plotted in model identification step to capture the autocorrelation properties. Normally, several potential models was identified to match the empirical autocorrelation patterns with the theoretical. Box [17] suggested that by using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) which generated from the sample data be the essential tools to figure the potential order of ARIMA model.

Moreover, Box-Cox of transformation was used to make the time series become stationary. This due to the fact that stationary was the fundamental condition for building out ARIMA model in order to make sure the mean was constant over the time. The equation (3) showed the power of transformation or logarithmic formula that using when the variance not stationary. Differencing was undergoing eliminate the trend and stabilize the variable before a potential ARIMA model fitted when the ACF and PACF represented the trend and heteroscedasticity.

$$y^\lambda = \begin{cases} \frac{y^\lambda - 1}{\lambda}, & \lambda \neq 0 \\ \ln y, & \lambda = 0 \end{cases} \quad (3)$$

where λ is a parameter of Box-Cox Transformation, and y^λ is transformation calculation.

Once a potential model was build, the estimation of model parameters is go forward to minimize the measurement error. The p -value of parameters in model must be less than α -value (0.05) and the L-Jung Box value greater than 0.05. After that, diagnostic checking was the last step of model building to measure the model adequacy. Plot of the residuals and diagnostic statistics used to examine the goodness of fits of tentative model to the historical data. The alternative tentative model have to identified again by following the steps of model identification and parameter estimation with the help of information from diagnostic checking.

These three steps of model building process was repeated until the satisfaction model was produced. The final satisfaction model was using for prediction process.

2.2. Support Vector Machines Regression (SVM)

Support Vector Machines was propose by Vapnik in 1995 [11]. According to Deng *et al.* (2012), SVM is classified into two major class which are classification (ν -SVC and C -SVC) and regression (ν -SVR and ε -SVR). Based on the risk minimization principle, SVM look for reducing the upper bound of the generalization error take place of the empirical error [18]. The SVM regression was formulated as below:

$$f(x) = \langle w, x \rangle + b \quad (4)$$

The coefficients w and b are measured by minimize

$$R(C) = C \frac{1}{N} \sum_{i=1}^N L_\varepsilon(d_i, y_i) + \frac{1}{2} \|w\|^2, \quad (5)$$

$$L_\varepsilon(d, y) = \begin{cases} 0 & \text{for } |f(x) - y| < \varepsilon \\ |f(x) - y| - \varepsilon & \text{otherwise} \end{cases}, \quad (6)$$

where C and ε are prescribed parameters, $L_\varepsilon(d, y)$ is called the intensive loss function, d_i is the actual stock price in the i^{th} period, $C \frac{1}{N} \sum_{i=1}^N L_\varepsilon(d_i, y_i)$ is the empirical error term, and $\frac{1}{2} w^2$ is flatness of the function.

Parameter C evaluated the trade-off between the empirical risk and the flatness of the model. Variables ξ and ξ^* with positive slack represented the distance from the actual values to the relevant boundary values of ε -tube. Equation (7) was transformed to the following formation:

Minimize:

$$R(w, \xi, \xi^*) = \frac{1}{2} w w^T + C^* \sum_{i=1}^N (\xi_i + \xi_i^*) \quad (7)$$

with the conditions:

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \xi_i^*,$$

$$w\phi(x_i) + b_i - d_i \leq \varepsilon + \xi_i,$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, 2, \dots, N.$$

After that, introducing Lagrangian multipliers and maximizing the dual function of equation (8) and changed it to the following form:

$$R(\alpha_i - \alpha_i^*) = \sum_{i=1}^N d_i (\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^N (\alpha_i - \alpha_i^*) - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N (\alpha_i - \alpha_i^*) \times (\alpha_j - \alpha_j^*) K(x_i, x_j) \quad (8)$$

with the conditions

$$\sum_{i=1}^N d_i (\alpha_i - \alpha_i^*) = 0,$$

$$0 \leq \alpha_i \leq C, \quad i = 1, 2, \dots, N.$$

$$0 \leq \alpha_i^* \leq C, \quad i = 1, 2, \dots, N.$$

In equation (9), α_i and α_i^* are called Lagrangian multipliers. They satisfy the equalities, $\alpha_i \times \alpha_i^* = 0$,

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) K(x, x_i) + b$$

(9)

where $K(x, x_i)$ represented kernel function.

The kernel function value was equivalent to inner product of vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$ such that $K(x, x_i) = \phi(x_i) \times \phi(x_j)$. Any function that fulfil Mercer's condition [11] can used as Kernel function.

2.3. Hybrid model

The behaviour of daily rubber price is difficult to capture. Therefore, a combination of linear and nonlinear model which was a good alternative to forecast daily rubber prices. Both ARIMA and SVM model have different data characteristics which ARIMA is linear model and SVM is nonlinear model. Hence, a hybrid model was proposed in this study for capturing both ARIMA component and SVM component. Thus, hybrid model able to modified the linear and nonlinear patterns in the sample data with improved the overall forecast performance. The hybrid model, Z_t represented as follow:

$$Z_t = Y_t + N_t, \quad (10)$$

where Y_t is the linear part of hybrid model, N_t is the nonlinear part of hybrid model, and both Y_t and N_t are estimated from the data set. \hat{Y}_t is the forecast value of ARIMA model at time t . Let ε_t present the residual at time t which obtain from ARIMA model, then

$$\varepsilon_t = Z_t - \hat{Y}_t \quad (11)$$

The residuals were modeled by the SVM:

$$\varepsilon_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-n}) + \Delta_t \quad (12)$$

where f is nonlinear function modelled by the SVM and Δ_t is random error. Thus, the hybrid forecast model is

$$\hat{Z}_t = \hat{Y}_t + \hat{N}_t \quad (13)$$

where \hat{N}_t is the forecast value of equation (12).

2.4. Evaluating forecast accuracy

The Mean Forecast Error (MFE), Root Mean Square Error (RMSE), and Correlation Coefficient (r) use to determine the accuracy of the forecast values compare to the actual values.

$$MAE = \frac{1}{n} \sum_{i=1}^n |F_i - A_i| = \frac{1}{n} \sum_{i=1}^n |e_i| \quad (14)$$

$$MFE = \frac{1}{n} \sum_{i=1}^n (A_i - F_i) \quad (15)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|A_i - F_i|}{|A_i|} \times 100 \quad (16)$$

$$RMSE = \sqrt{\frac{1}{n} \left[\sum_{i=1}^n (F_i - A_i)^2 \right]} \quad (17)$$

$$r_{zy} = \frac{S_{zy}}{S_z S_y} \quad (18)$$

where A_i is the actual observation time series, F_i is the fitted observation time series, n is the number of observation data points, z is the forecast variable, y as the actual variable, S_{zy} as the sample covariance between variable Z and Y , S_z as the standard deviation of variable Z , and S_y as the standard deviation of variable Y .

3. Forecasting of bulk latex price

Table 1. Evaluating forecast accuracy of ARIMA models of bulk latex

Model	MAE	MFE	MAPE	RMSE	r
ARIMA (1,1,3)	2.4918	0.1168	0.3831	3.2144	0.1441
ARIMA (3,1,1)	2.58024	-0.5783	0.3966	3.1036	0.1365
ARIMA (3,1,2)	2.68017	-0.6875	0.4128	3.1605	0.1703

The Table 1 shown the evaluated of forecast accuracy of ARIMA models for the Bulk Latex. The ARIMA (3,1,1) model had the smallest vaue of RMSE with 3.1036 among others, but the RMSE values of ARIMA (1,1,3), ARIMA (3,1,1) and ARIMA (3,1,2) models were compaitive result due to the values were almost closely to each others.

However, the ARIMA (1,1,3) model proved the lowest of MFE (0.1168) among other ARIMA models which meant that ARIMA (1,1,3) model was under forecasted with 11.68% to the actual values compared to ARIMA (3,1,1) which over forecasted 57.83% and similar to ARIMA (3,1,2) with 68.75%. Moreover, the MAPE and MAE values for ARIMA (1,1,3) was the smallest among other models too with 0.3831 and 2.4918 respectively. These meant that the differences between the forecast values produced by ARIMA (1,1,3) with actual prices was the smallest.

On the others hand, the r value for ARIMA (3,1,2) was recorded the highest (0.1703) among other. By the way, the differences between r value was small for each models meant it were compaitive. Thus, the ARIMA (1,1,3) model was the best model of Bulk Latex for ARIMA forecasting approach.

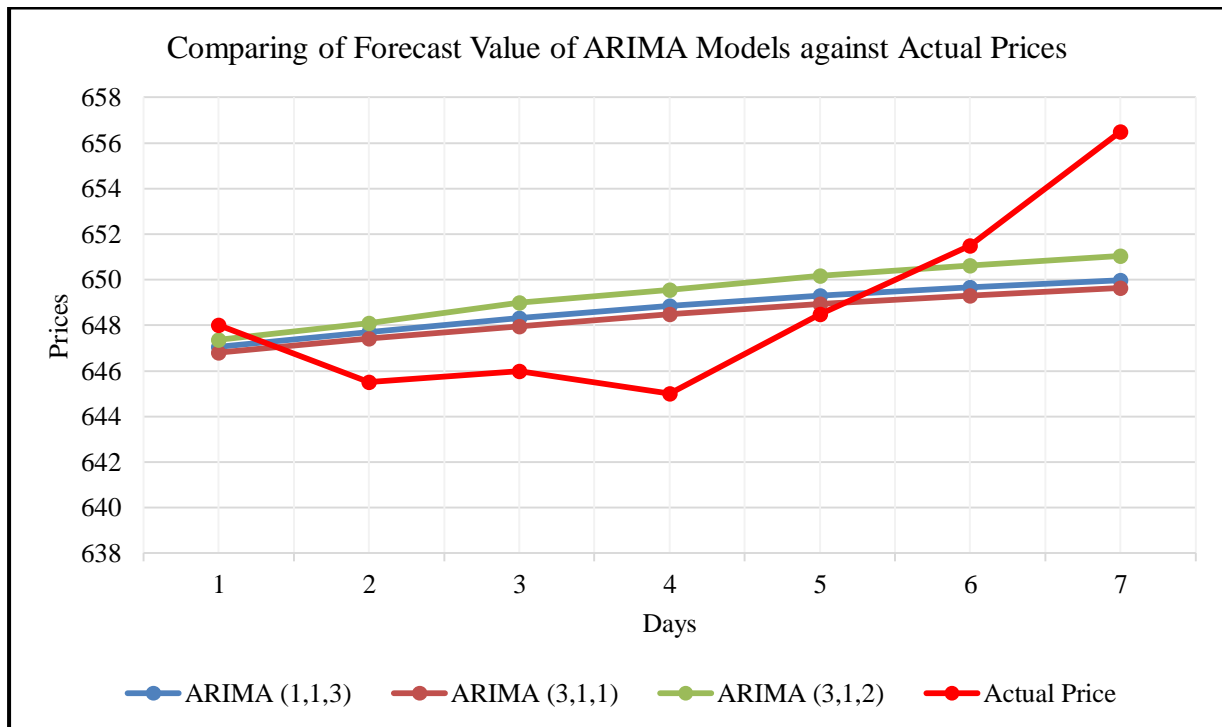


Figure 1. Comparing of forecast value of ARIMA models against actual prices

The Figure 1 shows the comparisons of the forecasted ARIMA models against the actual bulk latex prices. The forecasted value of ARIMA (3,1,2) model closed to the actual prices and this had been proved in Table 4.4. On the other hands, the ARIMA (1,1,3) model has the smallest value of MFE (0.1168). Besides that, the forecast values for ARIMA models were plot as straight line and increase continuously. Moreover, the structure of ARIMA models was remand similar by any changing of the Moving Average (MA) and Autoregressive (AR) values. In addition, the forecasted value of ARIMA models in Day 1, Day 5, and Day 6 were closing to the actual prices in that days. However, the actual prices was fluctuated from Day 1 to Day 4 and rose constantly until Day 7.

Table 2. Evaluating forecast accuracy of SVM models of bulk latex

Model	MAE	MFE	MAPE	RMSE	<i>r</i>
SVM Model 1	3.3838	-1.1341	0.5219	4.1696	0.9979
SVM Model 2	3.2578	-1.3692	0.5026	4.1952	0.998
SVM Model 3	3.1755	0.1662	0.489	3.9522	0.9981

The Table 2, the result shown shown the evaluated of forecast accuracy of SVM models for the Bulk Latex. The SVM Model 3 had the highest *r* value with 0.9981. However, the SVM models have the compativite result on the *r* which the values were closing to each others with the differences value of 0.0001.

The SVM Model 3 was the best forecast model among the others which has the lowest MFE value with 0.1662 which meant it was under forecast with 16.62% to the actual value only. Besides that, the SVM Model 3 had the smallest MAPE and MAE values with 0.4890 and 3.1755 respectively too.

This meant that the differences between the forecast values produced by SVM Model 3 with actual prices was the smallest. Besides that, it had the lowest RMSE value with 3.9522 too. The RMSE value meant the SVM Model 3 had the most accurate of the forecast ability due to the smallest value compared to others. Thus, it was the best model of Bulk Latex for SVM forecasting approach.

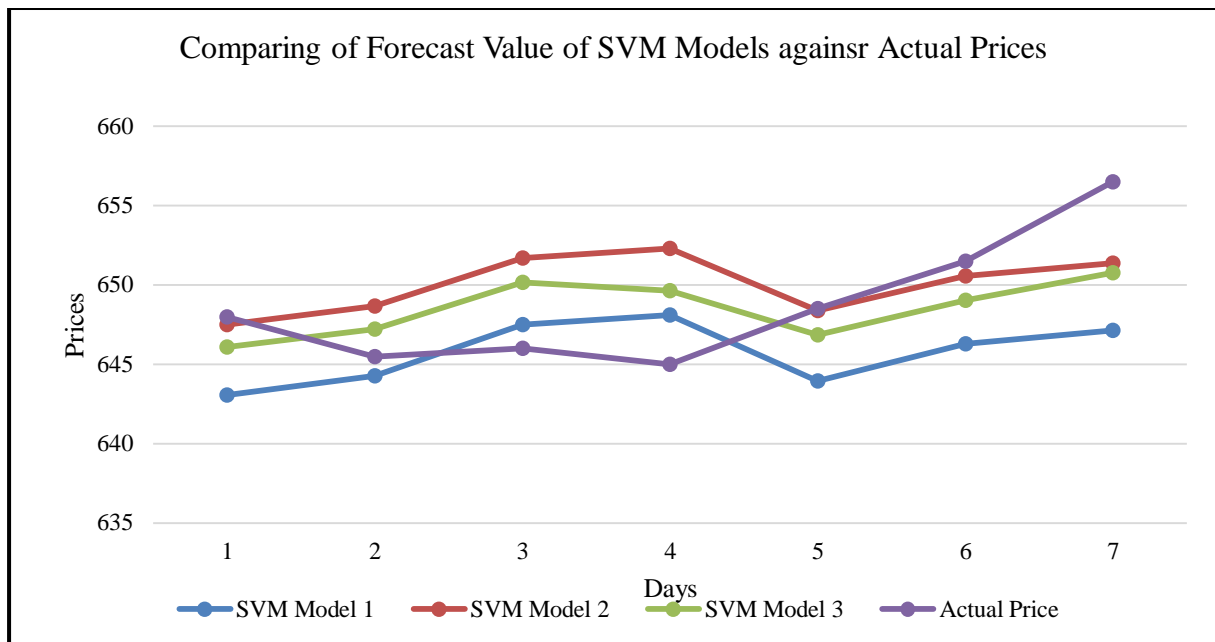


Figure 2. Comparing of forecast value of SVM models against actual prices

The Figure 2 displays the comparisons of forecasted SVM models against actual bulk latex prices. The forecasted values that produced by SVM models was fluctuated. The SVM Model 3 was the best forecast model among others with the closest value of forecast in Table 4.6 and the smallest values of MFE, RMSE, MAPE and MAE in Table 4.7. Moreover, the forecasted value of SVM Model 2 in Day 1, Day 5, and Day 6 were closing to the actual prices. However, the forecasted value of SVM Model 1 in Day 2 and Day 3 were closing to the actual prices in that days. Besides that, the structure of SVM models was remain similar by any changing of the parameter of Capacity, Nu, Kernel (Gamma).

Table 3. Evaluating forecast accuracy of Hybrid models of bulk latex

Hybrid Model	MAE	MFE	MAPE	RMSE	r
Hybrid Model 1	3.1412	-0.4693	0.4829	3.9425	0.9977
Hybrid Model 2	3.1552	-0.5395	0.4850	3.9577	0.9977
Hybrid Model 3	2.2909	0.0631	0.3535	4.5556	0.9976

The Table 3 shown the evaluated of forecast accuracy of hybrid models for the Bulk Latex. The results of r for Hybrid Model 1, 2, and 3 were very competitive due to the small difference for each others. The SVM Model 1 had the smallest RMSE value with 3.9425 among others. Hence, SVM Model 1 had the high accuracy of the forecast ability.

However, the Hybrid Model 3 model was the best hybrid models based on its had the smallest MFE value. This mean that it was under forecasted 6.31% only compared to others and the differences between the forecast values produced by Hybrid Model 3 with actual prices was the smallest. The MAPE and MAE values of Hybrid Model 3 was the smallest with 0.3535 and 2.2909 respectively among other Hybrid models too.

This meant that the differences between the forecast values produced by SVM Model 3 with actual prices was the smallest. Besides that, it had the lowest RMSE value with 3.9522 too. The RMSE value meant the SVM Model 3 had the most accurate of the forecast ability due to the smallest value compared to others. Thus, it was the best model of Bulk Latex for SVM forecasting approach.

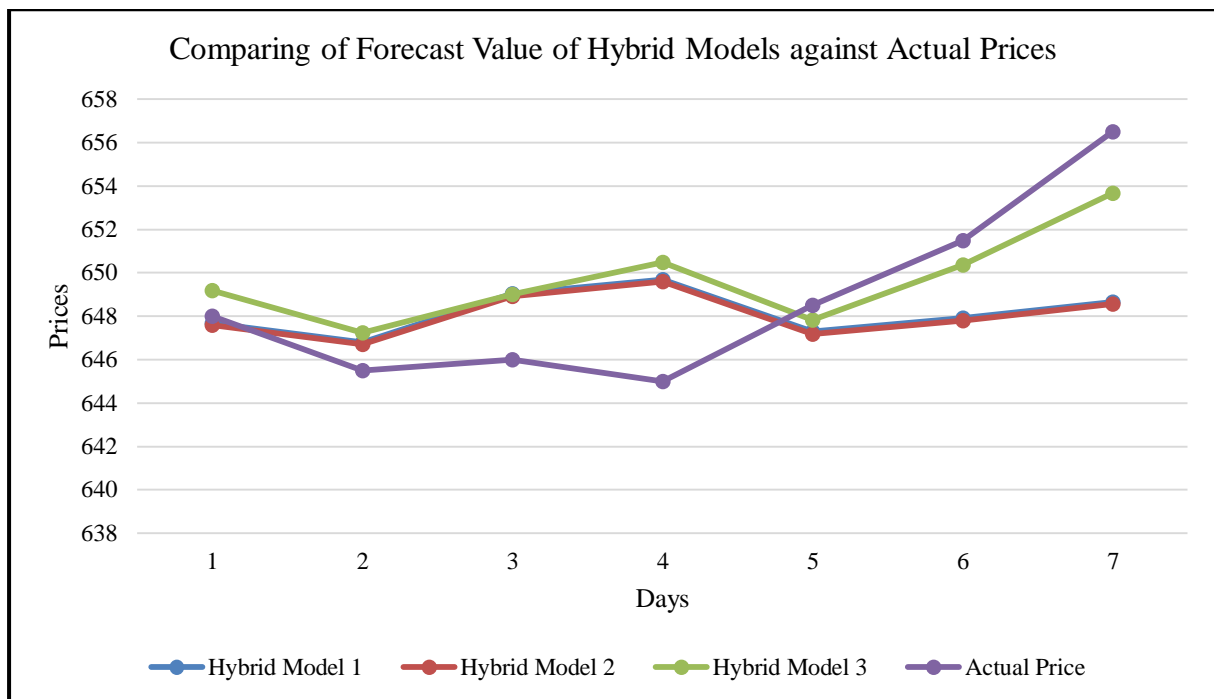


Figure 3. Comparing of forecast value of Hybrid models against actual prices

The Figure 3 shows the comparisons of forecasted Hybrid models against actual bulk latex prices. The forecast values that produced by Hybrid models were fluctuated. The forecast value of Hybrid Model 2 was the closest to actual prices in Table 4.8. However, the forecast value of Hybrid Model 1 was almost similar to Hybrid Model 2 where there were allocating the same position in the graph of Figure 4.13. On the other hands, the Hybrid Model 3 was the best forecast model among others with the smallest MFE, MAPE and MAE values in Table 4.9. In addition, the forecasted value of Hybrid Model 1 and Hybrid Model 2 in Day 1 and Day 2 were closing to the actual prices in that days. The forecasted value of Hybrid Model 3 in Day 5, Day 6 and Day 7 were closing to the actual price in that day.

Table 4. Comparison the Forecast Accuracy between the ARIMA, SVM, and Hybrid models.

Model	MAE	MFE	MAPE	RMSE	<i>r</i>
ARIMA					
ARIMA (1,1,3)	2.4918	0.1168	0.3831	3.2144	0.1441
ARIMA (3,1,1)	2.5802	-0.5783	0.3966	3.1036	0.1365
ARIMA (3,1,2)	2.6802	-0.6875	0.4128	3.1605	0.1703
SVM					
SVM Model 1	3.3838	-1.3692	0.5219	4.1952	0.9980
SVM Model 2	3.2578	-1.1341	0.5026	4.1696	0.9979
SVM Model 3	3.1755	0.1662	0.4890	3.9522	0.9981
Hybrid					
Hybrid Model 1	3.1412	-0.4693	0.4829	3.9425	0.9977
Hybrid Model 2	3.1552	-0.5395	0.4850	3.9577	0.9977
Hybrid Model 3	2.2909	0.0631	0.3535	4.5556	0.9976

Table 4 displayed the comparison of forecast accuracy between the ARIMA, SVM and Hybrid models. The Hybrid Model 3 was the best forecast model for Bulk Latex prices due to it had the

smallest MFE value with 0.0631 compared to other models. It was under forecasted of 6.31% to the actual prices of Bulk Latex. Moreover, the value of MAPE and MAE of Hybrid Model 3 were the smallest among other models with 0.3535 and 2.2909 too. This meant that the differences between the forecast values produced by Hybrid Model 3 with actual prices was the smallest compared to all forecast models. By combining the ARIMA and SVM models by hybridizing them was able to reduce the forecast error which had been shown in MAE value of Hybrid model 3.

Besides that, the r value for SVM and Hybrid models were very competitive and this situation for RMSE value of ARIMA, SVM and Hybrid models. Thus, the Hybrid Model 3 was considered as the best forecast model for Bulk Latex prices among other models.

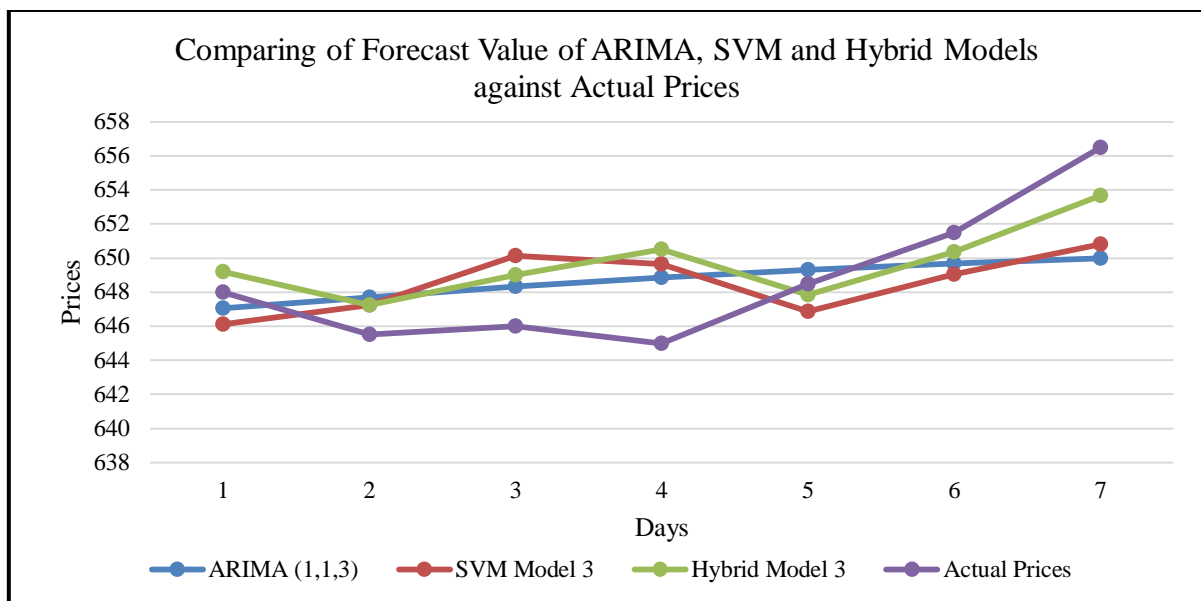


Figure 4: Comparing of forecast value of ARIMA, SVM, and Hybrid models against actual prices

Figure 4 displayed the comparisons of forecasted ARIMA, SVM, and Hybrid models against the actual bulk latex prices. The forecast values of SVM and Hybrid models were more fluctuated compared to ARIMA models which was straight line from the graph above. The Hybrid Model 3 was the best forecast model among others due to the smallest MFE, MAPE and MAE values compared to ARIMA (1,1,3) model and SVM Model 3 in Table 5.0.

Besides that, the forecasted value of ARIMA (1,1,3) model in Day 1 was closing to the actual prices in that days. However, the forecasted value of Hybrid Model 3 in Day 5, Day 6 and Day 7 were closing to the actual price.

4. Conclusion and discussion

The comparison results for ARIMA and SVM models will presented in section 3. The results showed that SVM gives better results than ARIMA models due to the fact that SVM model has higher value of correlation coefficients. This is because of the SVM method having better forecasting approach compare to ARIMA method based on the theoretical [12], due to SVM model is able to capture the nonlinearity and non-stationarity better than ARIMA model in the data set.

In order, the hybrid method by combining the ARIMA and SVM models will produce the best model of Bulk Latex for forecasting approach with the smallest MFE, RMSE, and highest correlation coefficient values. This is because hybrid method able to improve the accuracy and reduces the errors [14,19]. Therefore, the Hybrid Model 3 is the best forecast model that produced by Hybrid method for Bulk Latex prices with the smallest MAE, MFE, MAPE values with 2.2909, 0.0631, and 0.3535 respectively among other models.

The one of limitations of this research is this sample size for the Bulk Latex data set is able for short term forecast only. This is because this study was using 2 years data which contain 488 prices of day from January 2015 until December 2016. Therefore, the constant values will be appear when long term forecast proceed. Moreover, there will have many important information being lost due to the 2 years data being used.

Besides that, the parameters for SVM model are unknown and the step of obtain the optimal parameter and Kernel Function have to repeat many time until the satisfaction model being generate by trials-and-error approach. This is the same situation for ARIMA method too for generating the parameter of *MA* and *AR* to obtain the smallest *p*-value and highest L-Jung Box value by visual inspection on ACF and PACF plots

In addition, some information may being lost during the process of Hybrid method. This is because the process of hybrid method is separate into two part which is ARIMA method and SVM method. First, the ARIMA method is go through and get the residuals. Then, the residuals is substituting into SVM method. Therefore, there may had some information being lost during the process of ARIMA method due to this method have to transform from non-linearity to linearity.

The recommendation that suggest for further study is increasing the sample size. By increasing the sample size of data set, the forecast accuracy of forecast method will be improve due to the more information involved for time series forecast. Besides that, the variability of the data set will be reduce too because of the chance to obtain the extreme values will be decrease. Moreover, the observe value for the statistics will be group more closely to the mean of the sampling distribution.

Moreover, not all the hybrid methods can attain the researcher predictive forecasting performances which has been verified by previous study because difference types of time series data set has difference appropriate forecast methods can proceed for it. Besides that, the external variables that include the rubber prices should be determine and eliminate for generate more accuracy forecast models.

Lastly, the SVM model propose with the Genetic Algorism (GA) and Particle Swarm Optimization (PSO) which this two methods are able to determine the suitable parameter of SVM model (Capacity, Nu and Gamma).

5. References

- [1] Burger K, Smit H and Vogelvang B 2002 Exchange Rates and Natural Rubber Prices: The Effect of the Asian Crisis pp 4-5
- [2] Shamsudin M N and Arshad F M 2002 Short Term Forecasting of Malaysian Crude Palm Oil Prices. *Universiti Putra Malaysia: Master's Thesis*
- [3] Mesike C S 2012 Short term forecasting of Nigerian natural rubber export *Wudpecker Journals of Agricultural Research* **1** 10 pp 396-400
- [4] Pattranurakyothin T and Kumnungkit K 2012 Forecasting Model for Para Rubber's Export Sales *KMITL Sci. Technol. J* **12** 2 pp 198-202
- [5] Padhan P C 2012 Application of ARIMA model for forecasting agricultural productivity in India *Journal of Agriculture and Social Sciences* **8** 2
- [6] Assis K, Amran A and Remali Y 2010 Forecasting cocoa bean prices using univariate time series models *Researches World* **1** 1 pp 71
- [7] Khin A A and Mohamed Z A 2008 Natural rubber price forecasting in the world market. *Paper in agriculture sustainability through participative global extension, Putrajaya* pp 15-19
- [8] Conejo A J, Plazas M A, Espinola R and Molina A B 2005 Day-ahead electricity price forecasting using the wavelet transform and ARIMA models *IEEE transactions on power systems* **20** 2 pp 1035-1042
- [9] Pai P F and Lin C S 2005 A hybrid ARIMA and support vector machines model in stock price forecasting *Omega* **33** 6 pp 497-505
- [10] Vapnik V N and Chervonenkis A Y 1982 Necessary and sufficient conditions for the uniform convergence of means to their expectations *Theory of Probability and Its Applications* **26** 3 pp 532-553

- [11] Vapnik V 1995 The nature of statistical learning theory. 1st ed. *New York: Springer science and business media*
- [12] Niu B, Lu W C, Yang S S, Cai Y D and Li G Z 2007 Support vector machine for SAR/QSAR of phenethylamines *Acta pharmacologica sinica* **28** 7 pp 1075
- [13] Auria L and Moro R A 2008 Support Vector Machines (SVM) as a Technique for Solvency Analysis (No. 811) *DIW Berlin: German Institute for Economic Research* pp 8
- [14] Winkler R L and Makridakis S 1983 The combination of forecasts *Journal of the Royal Statistical Society Series A (General)* pp 150-157
- [15] Armstrong J S 2001 Principles of forecasting: a handbook for researchers and practitioners *United States of America: Kluwer Academic Publishers* **30**
- [16] Kenny G, Meyley A and Quinn T 1998 Forecasting Irish inflation using ARIMA models: An Introduction to ARIMA Modelling pp 4-5
- [17] Box G E, Jenkins GM, Reinsel G C and Ljung G M 2015 Time series analysis: forecasting and control. 5th ed *United State of America: John Wiley and Sons*
- [18] Deng N, Tian Y and Zhang C 2012 Support vector machines: optimization based theory, algorithms, and extensions *United States of America: CRC press*
- [19] Zhang F and Roundy R 2004 Improving Forecast Accuracy by Combination *School of Operations Research and Industrial Engineering Cornell University: Master's Thesis*