Possible Method for Monthly Natural Rubber Price Forecasting

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Abstract : Future price information is crucial not only for producers but also for other agribusiness actors. Price is a signal for them to make a decision regarding what to produce and when to sell including for natural rubber. For this reason, forecasting and selecting the best model becomes important. This study is aimed to analyze and select the possible forecasting methods for monthly natural rubber prices in Indonesia and World Markets. The univariate model of Double Exponential Smoothing, Decomposition, and ARIMA models are applied to forecast price data from 2012:1 – 2016:12. The selection of an accurate model is based on the lowest value of MAPE, MSD, and MAD. ARIMA is the possible methods for world rubber price forecasting while Double Exponential Smoothing should be applied for predicting domestic rubber prices because it allows for better predictive performance.

1 INTRODUCTION

Price is often used as a signal for producers to produce and or sell a commodity. Ribeiro, Sosnoski, and Oliveira (2010) stated that decision making requires information on how prices behave before the harvest is done. In addition, price fluctuations make agriculture a risky business as reported by Grega (2002) and Fafchamps (2000). Price is also often a determinant of the level of competitiveness of a product. Therefore, price determination will be able to assure the sustainability of farm business including rubber farming. Price uncertainty also causes difficulties in designing policies related to improving the welfare of farmers. Price uncertainty and price volatility also make farmers more vulnerable (FAO et al., 2011 and Sukiyono, et al., 2017) in the case of oil palm farmers). With these environmental conditions, price information in the future will be very important. Future pricing information requires accurate price forecasting. Any error in the prediction of price can cause a huge amount of revenue loss. This implies the importance of selecting the most probable forecasting model. Several analytical methods for forecasting are able to apply. Pandey and Upadhyay (2016) classify these forecasting methods into two categories: time series and simulation approach. Kirchgassner and Wolters (2007) and Pandey and Upadhyay (2016) state that a time series is defined as a set of numerical observations arranged in sequenced order or an even time interval. These data are historical data from market prices and collected at an equally spaced and discrete time interval. On the other hand, the simulation approach requires and generates a large amount of data and computationally intensive. This current paper applies a time series approach and is aimed at selecting a possible method for forecasting rubber price at world and domestic (Indonesia) markets.

Among time series forecasting models, three models are commonly used, that is, exponential smoothing, decomposition, and ARIMA. Exponential Smoothing method is designed based on a simple statistical model and does not use any variable other than the variable being forecast. Robert and Amir (2009) note that the exponential smoothing model has advanced significantly in the last few decades and established as one of the forecasting methods. Sudha et al., (2013) and Rani and Raza (2012) are among researchers using exponential smoothing models to forecast agricultural product and price. Another time series forecasting model is a decomposition approach. This approach involving additive and multiplicative decomposition separates trend and seasonal

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component from time series and computes the prediction whether by multiplying or adding to seasonal indices Saini, Saxena, and Surana (2017). This model has applied for various agricultural products, among others are Taru and Mshelia (2009) and Bergmann, O'Connor and Thümmel (2015). A comprehensive discussion on decomposition method is given by Dogum (2010) and Prema and Rao (2015). Finally, an Auto-Regressive Integrated Moving Average (ARIMA) model, introduced by Box and Jenkins (1976), is a technique for finding the most suitable pattern from a group of time series data, by utilizing past and present data to perform accurate forecasting. Weiss (2000) defines that ARIMA is a linear function of the previous actual values and random shocks. This model is also widely used in various agricultural products prices, such as chicken, pork, cabbage and other major agricultural prices (Hu Tao (2005) and Feng Liu et al. (2009)).

Each forecasting method discussed above also shows the advantages and disadvantages of each method. The problem is what the most accurate forecasting model for forecasting rubber prices in both the world market and the domestic market is. The selection of forecasting models so far has tended to use subjectivity considerations. There is no explanation from researchers regarding the selection and application of certain forecasting models for their research. Some researchers have tried to choose the best forecasting model using several models, including Sukiyono and Rosdiana (2018) on the price of rice at the wholesale level. From some of these studies, each different commodity and observation period has the best different model. That is, the forecasting model for commodities will not necessarily be appropriate or accurate for other commodities. Therefore, this study tries to determine the best model by comparing the accuracy of forecasting from the three models that are widely used so far, namely double exponential smoothing, decomposition, and ARIMA.

2 METHODS

This research used monthly data on rubber prices at domestic and world markets from 2012:1 – 2016:12 or 72 observations. Three-time series forecasting models are proposed namely, double exponential smoothing, additive and multiplicative decomposition, and ARIMA. These methods are explained in brief as follows:

2.1 Double Exponential Smoothing

Exponential Smoothing Model is a continuous improvement procedure for forecasting against the latest observational objects to produce a smoothed time series (Kumar and Gwada, (2015) and Jatra (2013)). This model focuses on exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the previous observations.

This study applies double exponential smoothing, also known as trend adjusted exponential smoothing. This model departs from improving a single exponential smoothing model by introducing the second equation with a second smoothing constant or second weight (α_2) and assuming monthly rubber price is influenced by the trend component. Kumar and Gwada, (2015) stated that introduction and selection of (α_2) having to consider (α_1). The double exponential model can be written as follows:

$$S_t = \alpha_1 X_t + (1-\alpha_1)(S_{t-1} + b_{t-1}) \quad (1) \text{ and}$$

$$b_t = \alpha_2 (S_t - S_{t-1}) + (1-\alpha_2) b_{t-1} \quad (2)$$

where, S_t = smoothened value at time period t; S_{t-1} = smoothened value at time period t – 1; α_1 = level smoothing constant; X_1 = actual price at time period t; b_t = trend estimate of the time period t; b_{t-1} = trend estimate of the period t-1; and α_2 = trend smoothing constant.

2.2 Decomposition Method

Decomposition methods are based on an analysis of the individual components of a time series, i.e., trend, seasonality, cycle, and error. In this approach, each component strength is estimated separately and then substituted into a model that explains the behavior of the time series. There are two decomposition methods: multiplicative and additive (Peng and Chu, (2009) and (Rajchakit, 2017). An additive decomposition model takes the following form:

$$Y_t = T_t + C_t + S_t + e_t \quad (3)$$

while a multiplicative decomposition model can be written as:

$$Y_t = T_t \times C_t \times S_t \times e_t, \quad (4)$$

where Y_t , the actual time series value at period *t*, is a function of four components: seasonal (S), cyclical (*C*), the trend (T) and an error component (*e*).

2.3 Arima

In applying an ARIMA model, this research follows Box-Jenkins methodology which involves four steps, namely identification, estimation, model checking, and forecasting. Dieng (2008) explains that the Box-Jenkins forecasting approach involves an interactive process between the forecaster and the data in terms of using diagnostic statistics to select the appropriate models. This approach also requires fewer data and has generally proved successful in practice. In general, according to Ekananda (2014), an ARIMA model is characterized by the notation ARIMA (*p*, *d*, *q*), where *p*, *d*, and *q* denote orders of Auto-Regression (AR), Integration (differencing) and Moving Average (MA), respectively. ARIMA is a parsimonious approach which can represent both stationary and non-stationary processes. Box and Jenkins (1976), an economic variable, Y, has a generating function which belongs to ARIMA (p, d, q) model is given by:

$$Y_t = \phi_1 Y_{t-1} + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \cdots + \varphi_q \varepsilon_{t-q} \quad (5)$$

where t = 1, 2, 3 ... T ε_t is an uncorrelated process with mean zero, ϕ_i and φ_i are coefficients (to be determined by fitting the model)

2.4 Forecasting Accuracy Measures

Three accuracy measures were calculated: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD). MAPE is a percentage point error while MAD and MSD are scale-dependent measures. Karim, Awala and Akhter (2010) noted that the smaller measurement values show more accurate forecasts since it produces minimum forecasting error. It should be noted that there was no shock variable at the period of study. It means that there is no unexpected change in a variable under analysis.

3 RESULTS AND DISCUSSION

3.1 Indonesian Rubber Profile

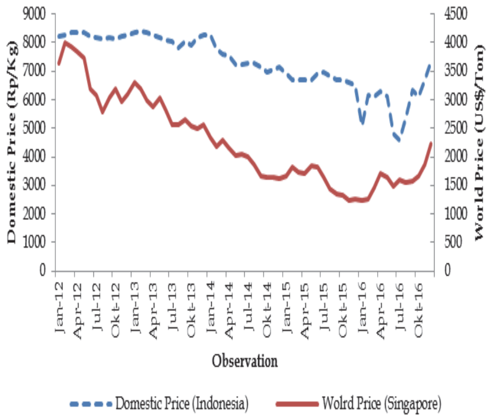


Figure 1: Domestic Rubber Price (Indonesia) and World (Singapore).

Indonesian Rubber Production in 2015 amounted to 34,340 tons and is estimated continues to increase until 2020 with a production of 40,449 tons (Karet outlook 2016). In terms of consumption, rubber consumption in 2020 is projected at 596 tons or increase over the next five years with an average of 0.85% per year within the period 2016 - 2020. Karet outlook (2016) also reported that for the next five years Indonesia is expected to surplus Rubber. If in 2016 Indonesia's rubber surplus amounted to 35,575 tons, this surplus is projected to continue to increase reaching 39,854 tons in 2020. The high production of rubber in Indonesia places Indonesia as one of the producers and exporters of rubber in the world. Indonesia in 2010 only able to contribute to the world rubber needs of 2.41 million tons of natural rubber or second after Thailand which amounted to 3.25 million tons (Purba, 2011). In addition, based on data from Perkebunan Perkebunan Nusantara, as reported by (Kompas, 11/09/2017), rubber production in Indonesia is currently recorded at 3.2 million tons per year. Of that amount, which can be absorbed domestically only 18 percent and the rest for export purposes. Indonesia's rubber exports are mostly directed to Vietnam, the Netherlands, the United States, and India.

Relation to the development of rubber prices, domestic and world price data presented in Figure 1 show a reasonably fluctuating movement. Recorded by Kompas, in 2011, the average price of rubber reached 5.58 US dollars per kilogram (kg), whereas in 2017 the average is only 1.2 US dollars per kg in the world market.

Figure 1 is not intended to compare the price level at two markets due to different unit price, but it is rather than to show the behavior pattern or tendency of rubber price. Figure 1 shows that world rubber prices and domestic rubber prices have likely similar patterns. The price of rubber in both markets tends to fall from the beginning of 2012 to the end of 2015 and started to increase in 2016. However, the downward rubber price trend in the Singapore market is sharper than in the domestic market.

Statistical summary of rubber price in domestic and world markets is presented in Table 1. Table 1 shows that rubber prices in the domestic market in the period January 2012 - 2016 moved from Rp 4,594.00/kg to Rp 8,408.00/kg with an average price of Rp 7,288.42/kg and Standard Deviation of 967.81. While in the world market, prices move from the US \$ 1,230.00/ton to the US \$ 4,000.00/ton with an average price of US \$ 2,260.00/ton.

Table 1: Statistical summary of Domestic and World Rubber Price.

Level	Mean	St. Dev.	Max	Min
Domestic Price (Rp./Kg)	7,288,42	967.81	8,408.00	4,594.00
World Price (US\$/Ton)	2,260.00	773.40	4,000.00	1,230.00

3.2 Model Forecasting Estimation

As discussed above, this article uses three forecasting models, namely exponential smoothing, ARIMA, and decomposition. The choice of the best model is used by three indicators of the accuracy of MAPE, MAD, and MSD where the model that has the lowest MAPE, MAD, and MSD values shows the most accurate forecasting method

3.3 Double Exponential Smoothing

This double exponential smoothing method uses two smoothing coefficients namely α_1 (smoothing constant) and α_2 (smoothing trend). This smoothing coefficient is determined by trial and error to produce the smallest error value (Stevenson, 2009). An indicator used to select the values of α and β is the Root Mean Square Error (RMSE), the best values of α and β are indicated by the smallest RMSE values. The results of forecasting rubber prices are presented in Figures 2 and 3, and Table 2.

For world rubber prices, the best values for α_1 and α_2 are 1.31913 and 0.02533 while for domestic rubber prices, the best values are 1.07791 and 0.02571. Looking at these values, both show almost the same value. This shows the similarity of data patterns between the two markets (see Figure 2).

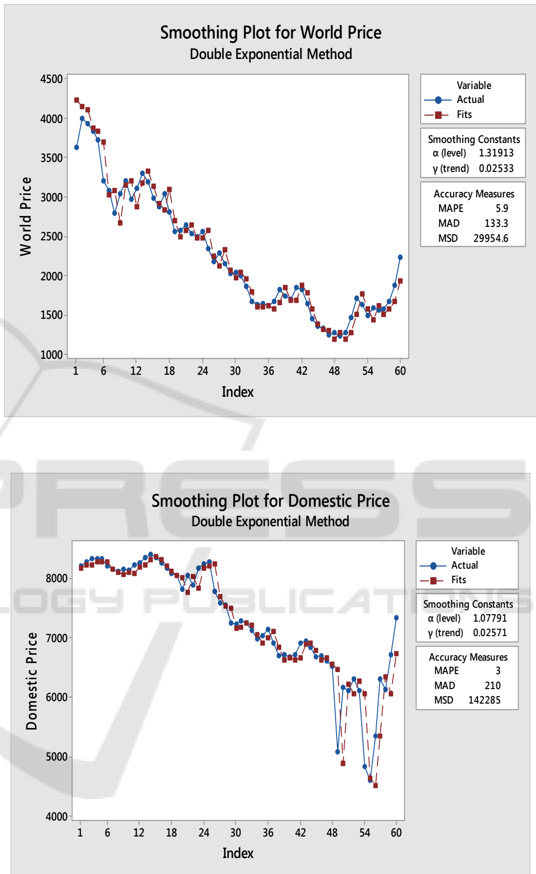


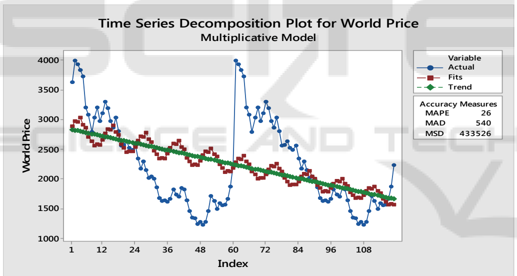
Figure 2: Smoothing Plots for World and Domestic Price.

Table 2: Forecasting results using Double Exponential Smoothing.

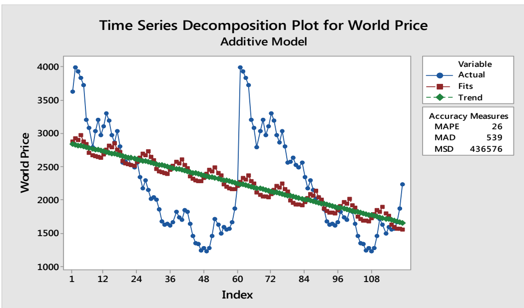
Prices	α_1	α_2	Accuracy Measure		
			MAPE	MAD	MSD
World Market	1.31913	0.02533	5.9	1.33	29,954.6
Domestic Market	1.07791	0.02571	3.0	210.00	142,285.0

3.4 Decomposition Model

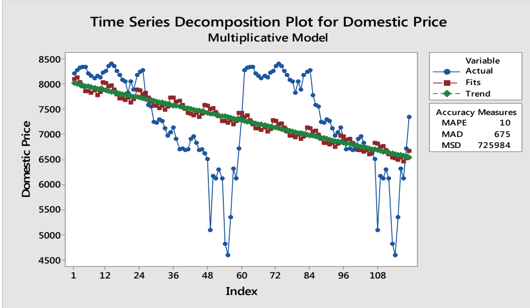
The estimated forecasting models for world rubber prices using decomposition approach are presented in Figure 3 (a) and (b) for multiplicative and additive respectively. Examining these figures, additive and multiplicative methods are likely to produce the same pattern and results. Both models also have a similar trend, namely, a downward trend with a comparable slope. By examining these results, both methods can be used to estimate the same level of accuracy. This conclusion is also supported by identical MAPE and MAD values (see Table 3). The MAPE values for both decomposition forecasting models are 26%, and the MAD values for both models are 540 and 539. This result concludes that it is multiplicatively more accurate than the additive in forecasting world rubber prices. However, looking at the MSD value, multiplicative has a smaller MSD value than additives. The MSD value of the multiplicative decomposition model is 433,526 while the additive MSD value is 436,576. This unconvincing result implies that forecasters can use additives or multiplicative to forecast world rubber prices.



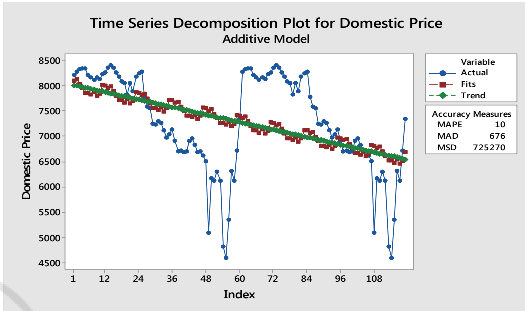
(a) Multiplicative Model



(b) Additive Model



(c) Multiplicative Model



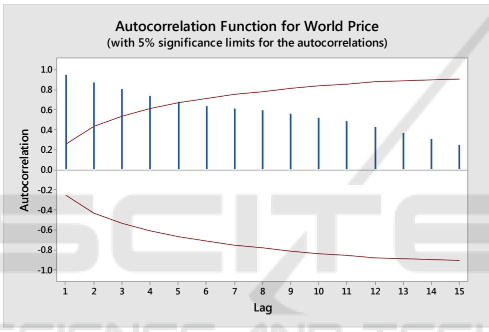
(d) Additive Model

Figure 3: Decomposition Model for domestic and World Price

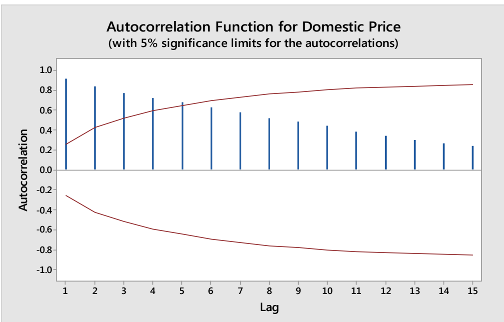
The unconvincing results are also indicated by the multiplicative and additive decomposition models for domestic rubber prices as presented in Figure 3 (c) and (d) as well as Table 3. Figure 3(c) and (d) also show that additive and multiplicative likely have similar in pattern and accuracy. Decomposition plots tend to have downward trends and similar cyclical patterns. Both additive and multiplicative decomposition seemingly have a similar slope. These results imply that the two forecasting models have the same level of forecasting accuracy. This means that these two decomposition models will produce nearly similar results. This conclusion is more convincing when viewed from the accuracy of measurement forecasting, namely, MAPE and MAD (Table 3). MAPE values for both additive and multiplicative are the same, i.e., 10%. Looking at MAD, multiplicative has the lower MSD value than additive, i.e., 675 and 676 for multiplicative and additive correspondingly. In addition, based on MSD value, the multiplicative decomposition model is less accurate than additive since multiplicative has a higher value than additive. This means that forecasters are better off applying an additive decomposition model to estimate future Indonesian rubber prices. By examining all accuracy measures used in this research, forecasters can apply an additive or multiplicative decomposition model for predicting domestic rubber prices due to inconclusive result.

Table 3: Accuracy for Forecasting of World and Domestic Rubber Prices using Decomposition Model

Decomposition Type		MAPE (%)	MAD	MSD
World Prices	Additive	26	539	436,576
	Multi-plicative	26	540	433,526
	Conclu-sion	Incon-clusive	Additive	Multipli-cative
Domestic Prices	Additive	10	676	725,270
	Multi-plicative	10	675	725,984
	Conclu-sion	Incon-clusive	Multipli-cative	Additive



(a) World Market



(b) Domestic Markets

Figure 4: Autocorrelation Function (ACF) for World Price and Domestic Price

3.5 ARIMA

Stationary test Autoregressive Integrated Moving Average (ARIMA) is used to complete the monthly price time series for 5 years. The use of time series cannot be separated from the problems of autocorrelation and partial autocorrelation calculations as illustrated in Figures 4 and 5.

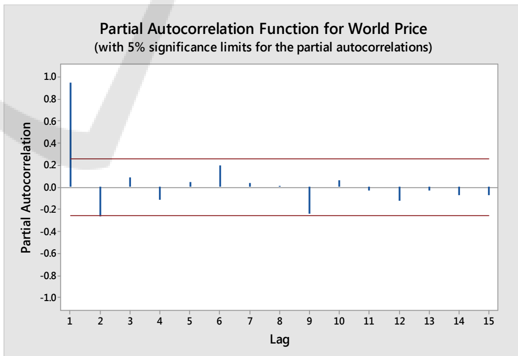
ACF and PACF in Figures 4 and 5 show that the series is not stationary because the ACF chart does not die down even though in the PACF there is 1 lag that is cut off. So, the series needs to be differentiated. This differentiation is performed with the Augmented Dickey-Fuller (ADF)

Table 4: Unit Root test with Augmented Dickey-Fuller (ADF)

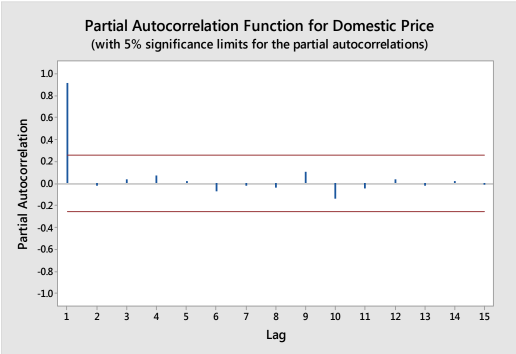
Data	t-statistic	Probability	Conclusion
World Market Price	1.648	0.452	Not Stationary *)
Domestic Market Price	1.122	0.699	Not Stationary *)

*) is corrected by differencing data accordingly.

Because both price data are not stationary, they are converted to stationary data on the first differencing. Then, the ARIMA model for domestic rubber prices is estimated. After comparing all the fit statistics, the best model is ARIMA (1,1,4) where all the parameters are significant at their respective significance levels (Table 5). Similar steps are also made for world rubber prices and ARIMA (1,1,4) is the best model.



(a) World Market



(b) Domestic Market

Figure 5: Partial Autocorrelation Function (PACF) for World Price and Domestic Price

Selecting the Possible method for Forecasting Rubber Prices. Table 6 presents a summary of accuracy measures for all forecasting models applied in this research. Among the parametric model used for world rubber prices, it is very difficult to decide which is the best forecasting model. If based on MAPE, ARIMA apparently is the best model with the lowest value MAPE in which ARIMA generates 5.31 % forecasting error.

However, if based on MAD and MSD, a double exponential model is the most accurate forecasting model. This model has the lowest value of MAD and MSD compared to other models. By following closely Bowerman *et al.* (2004); and Hyndman and Koehler (2006) to use MAPE for reasons of simplicity, the possible forecasting model for world rubber price is ARIMA.

Table 6: MAPE, MAD and MSD Value for each Forecasting Technique

Forecasting Model	MAPE (%)	MAD	MSD	Best Model
World Price of Rubber				
Double Exponential Smoothing	5,90	1.33	29,954.6	
ARIMA	5,31	14,51	50,630.0	ARIMA
Decompo-sition				
Additive	26	539	436,576.0	
Multiplica-tive	26	540	433,526.0	
Domestic Price of Rubber				
Double Exponential Smoothing	3.000	210	142,285	
ARIMA	3.381	27.162	145,695	Double Exponen-tial Smoothing
Decompo-sition				
Additive	10	676	725,270	
Multiplica-tive	10	675	725,984	

For domestic rubber prices, the best forecasting model is the Double Exponential Smoothing Model. This conclusion is based on two accuracy measures used in this paper, namely, MAPE and MSD. Double Exponential Smoothing model has the lowest MAPE and MSD value compared to other models even though this model has a higher value of MAD compared to ARIMA and Decomposition models. In order words, forecasters are better to apply double exponential smoothing model to predict domestic rubber prices in the future.

4 CONCLUSION

The main purpose of this article is to select the right model and forecasting model for predicting future rubber prices, both in the domestic market and the world market. Three types of forecasting methods were used for this study, i.e., Double Exponential Smoothing Method, Classical Decomposition Method and ARIMA. Forecasting method will be selected with minimum estimated error, that is minimum value MAPE, MAD, and also MSD. Although some decisions are not always unanimous, it is found that ARIMA and Double Exponential Smoothing models provide the most accurate prediction of rubber prices with most accuracy measures.

This finding also implies that depends only on one forecasting method usually cannot produce a reliable result. It is better to apply some methodologies. The methods successfully used in such commodities, like the regression analysis and smoothing techniques, are difficult to apply for other commodities. Such situations also give a great opportunity for other methods in which the role of human judgment and experience are higher. The result of the forecast also depends on the quality of the applied data.

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