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Decision Support System Using the Application of Tahani Model Fuzzy Logic

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ABSTRACT

The fuzzy logic of The Tahani model is described as a model used to process data searches, only that this model is based on operations in fuzzy set theory to obtain information that matches its data search criteria. In this study, the fuzzy logic of the Tahani model was applied to help the company PT. Lambarona Sakti in terms of determining recommendations for reordering Honda motorcycles with linguistic criteria against vehicle data that has definite characteristics. The determination of the recommendation of the vehicle to be rebooked from the main dealer is carried out by first doing the fuzzification stage, then determining the degree of membership, then a data search will be carried out based on the desired criteria, the final stage is determined recommendation based on the resulting fire strength value. How the determination of the fire strength value works can be done using the help of the Microsoft Excel application and automatically the results will be in accordance with the filling of the membership degree that has previously been done. 2 possible recommendations were obtained, namely there are recommendation results with all types of Honda motorcycles to be reordered and there are recommendation results with only a few types of Honda motorcycles to be reordered.

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1. INTRODUCTION

PT. Lambarona Sakti is a company engaged in the sales of Honda motorcycles in Aceh Besar. The sales of Honda motorcycles in this company cover several types. The owner of PT. Lambarona Sakti often feels uncertain when deciding which types of Honda motorcycles to reorder from the main dealer. This uncertainty is due to the highly varied monthly sales statistics for each type of Honda motorcycle sold by the company. So far, there are several types of Honda motorcycles that are most popular among consumers in the Aceh Besar area. One of them is the matic type, with a 90% interest rate, which is also profitable for the company. This is a highly desirable achievement for any business owner. Honda motorcycles come in many types and series. Due to this variety, reordering Honda motorcycles from the main dealer must be carefully considered because if the ordered types do not sell, it can lead to losses for the company. For example, if the reordered motorcycles are mostly the CBR type, which are difficult to sell, it will result in losses for the company (Nasir & Suprianto, 2017).

There are many methods that can be used in decision-making for reordering Honda motorcycles, one of which is using the Tahani model fuzzy logic. The Tahani model fuzzy logic is one fuzzy method that uses a standard database. Most standard databases are classified based on how the data is viewed by the user. In this standard database, the displayed data will appear as stored data. Research using the Tahani model fuzzy logic will show that this approach can produce accurate information regarding which types of Honda motorcycles are suitable for reordering by the company from the main dealer. This can serve as a decision support system for reordering Honda motorcycles at PT. Lambarona Sakti. The Tahani model fuzzy logic can be applied to evaluate types of Honda motorcycles using several combinations of criteria to obtain accurate results (Setiawan, 2020).

In previous research conducted by Nasir and Suprianto (2017) on "Fuzzy Logic Analysis for Selecting Honda Motorcycles Using the Mamdani Method," decision-making was carried out for three Honda types: beat, vario, and supra, starting with the fuzzification stage. It was followed by determining the implication functions, setting inference rules, and finally, the defuzzification stage using the centroid method to obtain the output value. The results showed that the recommended Honda type was vario, with a defuzzification result of 83.88% and a Matlab result of 79.4%. In Setiawan's (2020) research on "Decision Support System for Teacher Recruitment Using Tahani Fuzzy Logic," the steps were similar to the Mamdani method, starting from the fuzzification stage to determining the inference rules. However, in the Tahani fuzzy logic model, the defuzzification stage is not needed to obtain the output value. Instead, the fire strength value from each combination of criteria is used as the basis for decision-making. This fire strength value is the membership degree resulting from fuzzy set operations. Therefore, it can be concluded that the Mamdani method requires a defuzzification process to obtain the output value, whereas the Tahani fuzzy logic model does not.

This paper aims to analyze the Tahani model fuzzy logic to help PT. Lambarona Sakti decide which types of Matic Honda motorcycles to reorder from the main dealer based on purchase price, stock, and sales data. This approach aims to stabilize and increase the sales of Honda motorcycles in the company.

2. METHODS

The data used in this study includes the purchase price, stock, and sales of matic Honda motorcycles for the year 2021, obtained from PT. Lambarona Sakti. The tools and materials used in this study are Microsoft Excel 2013, which functions to calculate the values of the membership functions and the fire strength values. The variables used in this study are 3: purchase price, stock, and sales, with each variable defined by the following parameters:

- x_1 represents the purchase price variable.
- x_2 represents the stock variable.
- x_3 represents the sales variable.

Data collection is a process of gathering data conducted at PT. Lambarona Sakti. The collected data includes the purchase price, stock, and sales of matic Honda motorcycles that occurred at PT. Lambarona Sakti in 2021. After this data collection stage, data processing will be carried out to make decisions on reordering matic Honda motorcycles. The data can be seen in Table 1 below:

Table 1. Data

No.	Type	Purchase price	Stock	Sale
1	Beat sporty cbs	Rp9.620.000,-	154	149
2	Beat sporty cbs iss	Rp10.710.000,-	57	53
3	Beat sporty delux cbs iss	Rp10.824.000,-	233	233
4	Beat street	Rp10.780.200,-	43	41
5	Genio cbs	Rp10.697.800,-	4	1
6	Genio cbs iss	Rp10.419.200,-	12	8
7	Scoopy sporty/fashion	Rp11.772.600,-	461	461
8	Scoopy stylish/ prestige	Rp12.377.300,-	463	463
9	Vario 125 cbs	Rp12.224.900,-	24	15
10	Vario 125 cbs iss	Rp12.735.100,-	65	62
11	Vario 150 exclusive	Rp14.625.900,-	61	52
12	Vario 150 sporty/BK	Rp14.512.300,-	140	134
13	PCX 160 cbs	Rp20.445.200,-	42	41

14	PCX 160 abs	Rp23.620.000,-	14	14
15	ADV 150 cbs	Rp23.631.200,-	5	3
16	ADV 150 abs	Rp26.001.020,-	1	0

The data analysis and planning stage is a crucial phase in the development of a system. The steps to be used in this study are:

a. Fuzzification

From the data in Table 1, fuzzy sets will be formed. For the purchase price variable, the sets are cheap, medium, and expensive. For the stock variable, the sets are low, medium, and high. For the sales variable, the sets are low, medium, and high. The universe of discourse is determined by sorting the data from smallest to largest for each variable. The domain is based on the data of matic Honda motorcycles obtained from PT. Lambarona Sakti. The formation of fuzzy sets can be seen in Table 2 below:

Table 2. Formation of fuzzy sets

Variable	**Set**	**Universe**	**Domain**
Purchase	cheap	[9.620.000 , 26.001.020]	[9.620.000 , 14.625.900]
	medium		[12.735.100 , 20.445.200]
	expensive		[19.500.000 , 26.001.020]
Stock	low	[1 , 463]	[1 , 133]
	medium		[120 , 300]
	high		[281 , 463]
Sale	Low	[0 , 463]	[0 , 130]
	Mid		[120 , 300]
	High		[281 , 463]

b. Determining Membership Degrees

Membership degrees are derived from the data for each fuzzy set variable. The data values are then substituted into the membership functions for each variable, resulting in the membership degrees for all given membership functions.

The purchase price variable has 3 fuzzy sets: cheap, medium, and expensive. The cheap set uses a decreasing linear membership function (Figure 2.1), the medium set uses a triangular membership function (Figure 2.3), and the expensive set uses an increasing linear membership function (Figure 2.2). The stock variable has 3 fuzzy sets: low, medium, and high. The low set uses a decreasing linear membership function (Figure 2.1), the medium set uses a triangular membership function (Figure 2.3), and the high set uses an increasing linear membership function (Figure 2.2). The sales variable has 3 fuzzy sets: low, medium, and high. The low set uses a decreasing linear membership function (Figure 2.1), the medium set uses a triangular membership function (Figure 2.3), and the high set uses an increasing linear membership function (Figure 2.2).

c. Criteria Formulation

Selection criteria are formulated based on combinations of operations between fuzzy sets and their respective variables. Therefore, the number of criteria formed depends on the number of fuzzy variables and the sets used for each variable.

d. Determining Fire Strength Values

In this stage, fire strength values will be determined based on the desired criteria. Using the Tahani fuzzy logic model, fire strength values can be computed using Structure Query Language (SQL) as shown in equation (2.8).

e. Determining Recommendation Results

For the recommendation results, the option with a fire strength value greater than zero will be selected.

The data above was processed by following the following ARIMAX model forecasting procedure:

1) Get summary statistics.
2) Form a time series data plot.
3) Testing stationarity of variance and mean.
4) Identify the model by plotting the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) correlograms to obtain a tentative model.
5) Modeling data using the ARIMAX model.
6) Choose the best model based on the Akaike's Information Criteria (AIC) value. The model is considered relatively better if the AIC value is smaller.
7) Diagnose the best model from step 6 with 3 tests, namely white noise testing, error normality and parameter significance.
8) Measuring forecasting accuracy based on MAPE and RMSE values
9) Forecast IHSG data for the next 12 months and draw conclusions.

3. RESULT AND DISCUSSION

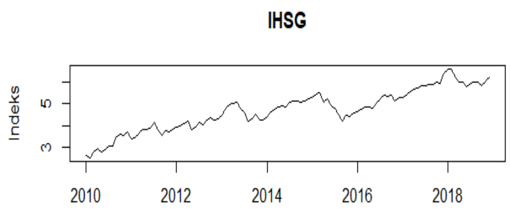
3.1.Descriptive Analysis

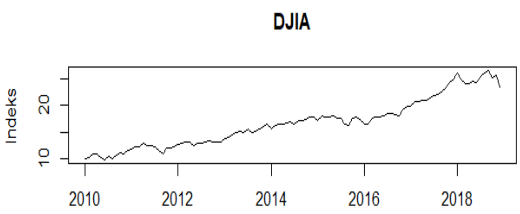
Summary statistics for IHSG, DJIA, N225, and SSEC data for 9 years, namely from 2010 to 2018, can be seen in the following Table 2.

Table 2. Statistics summary

Variable	Min	Average	Max
IHSG	2,549.03	4,702.50	6,605.63
DJIA	9,774.02	16,676.04	26,458.31
N225	8,434.61	15,188.97	24,120.04
SSEC	1,979.21	2,769.05	4,611.74

IHSG has an average share price of 4,702.54 with the lowest share price being 2,549.03 in February 2010, and the highest share price being 6,605.63 in January 2018. The DJIA index has an average share price of 16,676, 04 with the lowest share price being 9,774.02 in June 2010, and the highest share price being 26,458.31 in September 2018. The N225 Index has an average share price of 15,188.97 with the lowest share price being 8,434.61 in November 2011, and the highest share price was 24,120.04 in September 2018. The SSEC Index had an average share price of 2,776.38 with the lowest price being 1,979.21 in June 2013, and the highest share price being 4,611.74 in May 2015.





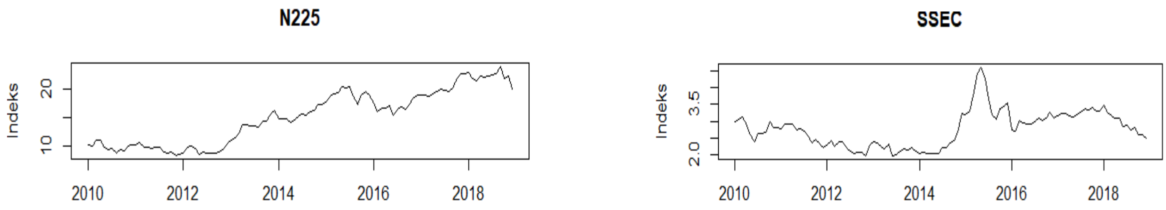


Figure 1. Plot of IHSG, DJIA, N225, and SSEC time series data

Data fluctuations for each variable can be seen in Figure 1. The Indonesian Composite Stock Price Index (IHSG) data plot has the form of a positive trend data pattern, with the data continuing to increase from year to year. The Dow Jones Industrial Average (DJIA) index data plot also has a positive trend data pattern, with DJIA index share prices also continuing to increase from year to year. The Nikkei 225 (N225) index data plot has stable data fluctuations from the beginning of 2010 to the end of 2012. However, at the beginning of 2013 the N225 index shows a positive trend until 2018. The Shanghai Stocks Composite Exchanges (SSEC) index data plot shows a negative trend, namely a decline from 2010 to 2014. In mid-2015, precisely in April and May, there was a very significant sudden increase in the SSEC index, until it reached its highest point in May 2015. The SSEC index experienced another significant decline in the same year in July 2015. The extreme movement of the Chinese stock index was caused by the turmoil in the Chinese stock market that year. At that time, China's economic growth was slowing or weakening, which was inversely proportional to the Chinese stock market index which was increasing rapidly.

3.2. ARIMAX Model

Stationarity testing in variance was carried out using Lambda BoxCox. Table 3 presents the lambda values. The lambda value can be estimated using a likelihood function.

Table 3. Lambda *Box-Cox* value

Variable	Lambda (λ) value
IHSG (Y)	0.315
DJIA (X_1)	-0.173
N225 (X_2)	-0.083
SSEC (X_3)	-0.447

The results show that all variables have a lambda value $\lambda \neq 1$ or not yet close to one. So it can be concluded that the data is not stationary regarding variance, so it is necessary to carry out transformations on the data. The transformation is carried out by powering the data as shown in Table 4. The power is obtained through trial and error until the lambda value $\lambda = 1$ or close to 1 is obtained. The type of transformation and the lambda value obtained are presented in Table 4.

Table 4. Box-Cox lambda values after transformation

Variable	transformation	Lambda (λ) value
IHSG (Y)	($y^{0.31}$)	1.027
DJIA (X_1)	($x_1^{-0.17}$)	1.007
N225 (X_2)	($x_2^{-0.11}$)	0.986
SSEC (X_3)	($x_3^{-0.11}$)	1.019

The lambda (λ) value of the four types of transformation is close to 1. All variables are stationary with respect to variance. Table 5 shows the results of the stationarity test on the mean. The four variables used in the research are not stationary in mean. This can be seen from the p-value > alpha (0.071 > 0.05), (0.323 > 0.05), (0.597 > 0.05), (0.577 > 0.05). So the decision is that we cannot reject H_0, meaning the data is not stationary in the mean. So differencing is needed in the data. The following are the results obtained after differencing the data.

Table 5. ADF test statistical value

Variable	Before differencing		After differencing	
	t-count	p-value	t-count	p-value
IHSG (Y)	-3.323	0.071	-5.046	0.01
DJIA (X_1)	-2.613	0.323	-5.425	0.01
N225 (X_2)	-1.952	0.597	-3.876	0.01
SSEC (X_3)	-2.000	0.577	-4.282	0.01

3.3. Model Identification

Model identification to determine the order of the ARIMA model is done by looking at the pattern of the ACF and PACF plots from stationary data. The data used to view the ACF and PACF plots uses IHSG data which is an endogenous variable. The plot of the ACF and PACF plots are as follows:

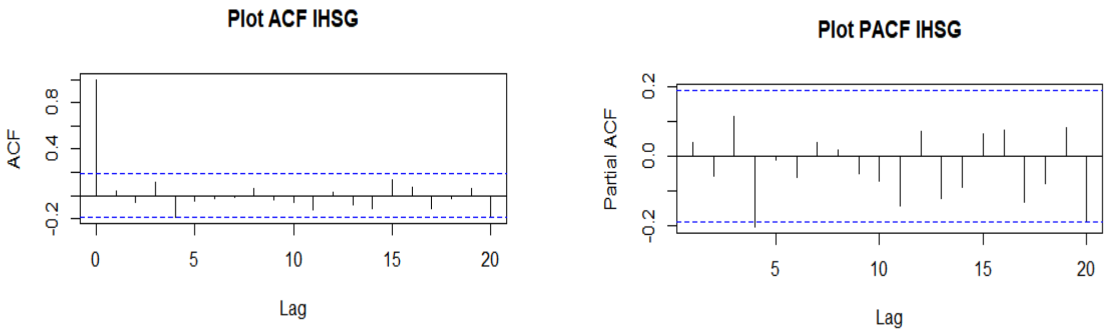


Figure 2. Plot ACF and PACF of IHSG data

Figure 2 shows that the ACF plot pattern of the IHSG data decreases rapidly after lag 0, and cuts off at the second lag. And the pattern of the PACF plot is truncated after the first lag. Based on the ACF plot, it can be seen that there is only one lag that crosses the line, namely the fourth lag. And in the PACF plot there is also one lag that crosses the line, namely also the fourth lag. Based on the results of the ACF and PACF plots, it is suspected that the appropriate ARIMA model for this data is the ARIMA model (4,1,4) with one differencing of the data. Because there is only one presumptive model, the ARIMAX model modeling starts with the tentative ARIMAX model (1,1,1), which is continued by selecting the best model from the 10 models that have been formed.

Table 6. ARIMAX model and AIC value

Model	Order	AIC
ARIMAX 1	(1,1,1)	1401.26
ARIMAX 2	(2,1,1)	1401.59
ARIMAX 3	(1,1,2)	1402.89
ARIMAX 4	(2,1,2)	1401.89

ARIMAX 5	(3,1,2)	1403.84
ARIMAX 6	(2,1,3)	1401.81
ARIMAX 7	(3,1,3)	1405.98
ARIMAX 8	(4,1,3)	1405.63
ARIMAX 9	(3,1,4)	1405.77
ARIMAX 10	(4,1,4)	1401.19

Table 6 is the AIC value of the 10 models that have been tried. Of the 10 models, there are 5 models that have the smallest AIC values, with the differences in AIC values not being much different or significant from each other, namely the ARIMAX 1, 2, 4, 6 and 10 models.

3.4. Model Diagnosis

White noise testing was carried out using the Ljung-Box test. Table 7 shows the results of the white noise test. These five models have fulfilled the white noise assumption. This order can be seen from the p-value produced by ARIMAX 1, 2, 4, 6 and 10 which is greater than $\alpha = 0.05$. Respectively, namely (0.875 > 0.05), (0.646 > 0.05), (0.728 > 0.05), (0.910 > 0.05), (0.745 > 0.05). So the decision is that we cannot reject H_0, meaning that the five models do not have autocorrelation between errors.

Table 7. Statistical results of the Ljung-Box test on the ARIMAX model (p,d,q)

Model	χ^2	p-value
ARIMAX 1 (1,1,1)	0.025	0.875
ARIMAX 2 (2,1,1)	0.212	0.646
ARIMAX 4 (2,1,2)	0.121	0.728
ARIMAX 6 (2,1,3)	0.013	0.910
ARIMAX 10 (4,1,4)	0.106	0.745

The error normality test was carried out using the Shapiro Wilk test. Table 8 is the test results.

Table 8. ARIMAX model error normality test statistics (p,d,q)

Model	W	p-value
ARIMAX 1 (1,1,1)	0.966	0.007
ARIMAX 2 (2,1,1)	0.970	0.016
ARIMAX 4 (2,1,2)	0.976	0.046
ARIMAX 6 (2,1,3)	0.985	0.136
ARIMAX 10 (4,1,4)	0.991	0.700

Table 8 shows that the ARIMAX 6 (2,1,3) and ARIMAX 10 (4,1,4) models are normally distributed models, this is because they have a p-value > $\alpha = 0.05$, namely (0.136 > 0 .05), (0.700 > 0.05) >. So the decision is that we cannot reject the null hypothesis. And it can be concluded that the ARIMAX 6 and 10 models have normal distribution errors. And the other three models, namely ARIMAX models 1, 2, and 4, produce p-values < α, respectively (0.007 < 0.05), (0.016 < 0.05), and (0.046 < 0.05). So the decision is to reject the null hypothesis. And it can be concluded that the error does not spread normally.

Parameter significance testing is used to determine whether the influence of a parameter in the model is significant or not. A parameter is said to have a significant influence if the p-value < $\alpha = 0.05$. Based on the results of previous tests, there are two models that meet the white noise and error normality assumptions, namely the ARIMAX 6 (2,1,3) and ARIMAX 10 (4,1,4) models. So it can be concluded that the two models are suitable for use for forecasting.

Test statistics for testing parameter significance using equation (2.14) obtained results as in Table 9.

Table 9. Estimation of ARIMAX model parameters (2,1,3)

Coefficient	Estimated Value	p-value	Significance
ϕ_1	0.664	0.000	Significant
ϕ_2	-0.895	0.000	Significant
θ_1	-0.630	0.000	Significant
θ_2	1.022	0.000	Significant
θ_3	-0.037	0.767	No
β_1	0.145	0.000	Significant
β_2	-0.025	0.342	No
β_3	0.095	0.293	No

Table 9 shows that there are three parameters that are not significant in the results of parameter significance testing in the ARIMAX model (2,1,3). This result can be seen from the p-value of these three parameters being greater than α = 0.05. The equation for the ARIMAX model (2,1,3) can be written as follows:

$$(1-B)^1(1+0{,}6637B-0{,}8950B^2)\,Y_t=(1-0{,}6299B+1{,}0219B^2+0{,}0371B^3)\,e_t+0{,}1446X_{1,t}-0{,}0252X_{2,t}+0{,}0949X_{3,t} \quad (1)$$

The following are the results of testing the significance of the ARIMAX (4,1,4) model parameters:

Table 10. Parameter estimation of the ARIMAX (4,1,4) model

Coefficient	Estimated Value	p-value	Significance
ϕ_1	1.069	0.000	Significant
ϕ_2	-0.365	0.013	Significant
ϕ_3	0.965	0.000	Significant
ϕ_4	-0.819	0.017	Significant
θ_1	-1.207	0.021	Significant
θ_2	0.473	0.000	Significant
θ_3	-1.207	0.000	Significant
θ_4	1.000	0.000	Significant
β_1	0.212	0.000	Significant
β_2	-0.051	0.040	Significant
β_3	-0.044	0.548	No

Table 10 shows that almost all parameters have a significant effect in the model. Except for the parameters of the SSEC stock index, which is a Chinese state stock. The decision can be seen from the resulting p-value of 0.548 > α = 0.05, so it cannot reject the null hypothesis, and the parameter is not significant. The equation for the ARIMAX model (4,1,4) can be written as follows:

$$(1-B)^1(1+1{,}0678B-0{,}3646B^2+0{,}9653B^3+0{,}8194B^4)\,Y_t=(1-1{,}2069B+0{,}4727B^2+1{,}2069B^3+1{,}0000B)\,e_t+0{,}2116X_{1,t}-0{,}0508X_{2,t}-0{,}0435X_{3,t} \quad (2)$$

The results of parameter significance testing from the two models above, the ARIMAX model (4,1,4) has only one insignificant parameter, and in the ARIMAX model (2,1,3) there are three insignificant parameters. So it can be concluded that the ARIMAX model (4,1,4) is better used for forecasting. In addition, the forecasting error value generated from the ARIMAX model (4,1,4) is smaller than the error value from the ARIMAX model (2,1,3).

3.5. Forecasting Accuracy Measurement and Data Forecasting

The measuring instruments used to calculate forecasting accuracy are mean absolute percentage error (MAPE) and root of mean square error (RMSE). The smaller the MAPE and RMSE values, the better the forecast results. From the results of diagnostic tests, there are two models that meet the assumptions, namely ARIMAX (2, 1, 3), and ARIMAX (4, 1, 4). Based on the results of forecasting accuracy measurements obtained, forecasting using the ARIMAX model (4,1,4) has MAPE and RMSE values smaller than the ARIMAX model (2,1,3) as seen in Table 11.

Table 11. MAPE and RMSE values

Model	RMSE	MAPE
ARIMAX (2,1,3)	151,374	2,643
ARIMAX (4,1,4)	144,539	2,512

Table 11 shows that forecasting using the ARIMAX model (4,1,4) produces better forecasts than using the ARIMAX model (2,1,3). IHSG 2019 data forecasting uses the ARIMAX model (4,1,4) by looking at the influence of the global stock price index, the resulting forecast is as in Table 11. Based on the forecast results, the highest share price of 6,958,419 occurred in November, and the lowest share price of 6,591,566 occurred in January.

Table 12. IHSG data forecast for 2019

Mounth	Forecast Data	Actual Data
January	6,591.57	6,197.87
February	6,777.02	6,552.06
March	6,788.14	6,468.62
April	6,908.24	6,485.72
May	6,623.36	6,458.12
June	6,924.87	6,277.29
July	6,956.26	6,281.18
August	6,873.80	6,385.26
September	6,866.52	6,331.15
October	6,795.66	6,163.98
November	6,958.42	6,225.81
December	6,856.79	6,299.54

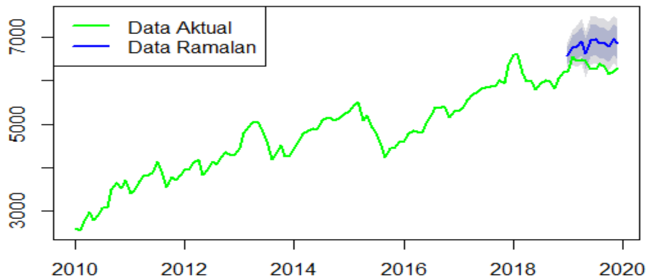


Figure 3. Plot data forecast results

Figure 3 shows IHSG forecast data for 2019. The results of the forecast can be seen on the blue line, IHSG experiences data fluctuations, which tends to show an upward trend in 2019.

4. CONCLUSION

The conclusion of this study is that the model used to forecast IHSG for 2019 is the ARIMAX model (4,1,4), with the following equation:

$$(1- B)^1(1+1{,}068B - 0{,}365B^2 + 0{,}965B^3 + 0{,}819B^4)\ Y_t = (1- 1{,}207B + 0{,}473B^2 + 1{,}207B^3+1{,}000B)\ e_t+0{,}212X_{1,t}-0{,}051X_{2,t}- 0{,}044X_{3,t}$$

The ARIMAX model (4,1,4) has better forecasting accuracy than other models, measured using MAPE and RMSE values of 2.512 and 144.539 respectively. The results of the IHSG data forecast for 2019 produce fluctuating data. The highest share price of 6,958,419 occurred in November, while the lowest share price of 6,591,566 occurred in January.

REFERENCES

Andiyasa, I. G. A., Purbawangsa, I. B. A., & Rahyuda, H. (2014). Pengaruh beberapa indeks saham dan indikator ekonomi global terhadap kondisi pasar modal Indonesia. *E-Jurnal Ekonomi dan Bisnis Universitas Udayana*, 44686.

Bodie, Z., Kane, A., & Marcus, A.J. (2006). *Investments*, Edisi Keenam. Salemba Empat, Jakarta.

Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *26*(2), 211-243.

BEI. (2010). Buku panduan indeks harga saham bursa efek Indonesia. *Jakarta: Bursa Efek Indonesia*.

Cools, M., Moons, E., & Wets, G. (2009). Investigating the variability in daily traffic counts through use of ARIMAX and SARIMAX models: assessing the effect of holidays on two site locations. *Transportation research record*, *2136*(1), 57-66.

Damodar, N. (2004). Basic econometrics: Student solutions manual for use with basic econometrics.-4th.

Fakhruddin, H. M., & Darmadji, T. (2011). Pasar Modal di Indonesia. *Edisi Ketiga, Penerbit Salemba Empat*.

Makridakis, S., Wheelwright, S. C., McGee, V. E., Andriyanto, U. S., & Basith, A. (1999). Metode dan Aplikasi Peramalan Jilid 1 Edisi Kedua. *Terjemahan oleh Ir. Hari Sumito. Jakarta: Bina Rupa Aksara*.

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015). *Introduction to time series analysis and forecasting*. John Wiley & Sons.

Mulyana, D. (2004). *Metodologi penelitian kualitatif: paradigma baru ilmu komunikasi dan ilmu sosial lainnya*. PT. Remaja Rosdakarya.

Nachrowi, D. N., & Usman, H. (2006). Ekonometrika: Pendekatan Populer dan Praktis Untuk Analisis Ekonomi dan Keuangan. *Jakarta: LPFE UI*.

Oktarina, D. (2015). Pengaruh beberapa indeks saham global dan indikator makroekonomi terhadap pergerakan IHSG. *Journal of Business & Banking*, *5*(2), 163-182.

Sungkawa, I., & Megasari, R. T. (2011). Penerapan ukuran ketepatan nilai ramalan data deret waktu dalam seleksi model peramalan volume penjualan pt satriamandiri citramulia. *ComTech: Computer, Mathematics and Engineering Applications*, *2*(2), 636-645.

WEI, W. W. (2006). Univariate and Multivariate Methods. *TIME SERIES ANALYSIS*.

Yaffee, R., & McGee, M. (2000). Introduction to Time Series Analysis and Forecasting: With Applications of SAS and SPSS Academic Press. *Inc, Orlando, FL, USA*.