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Intervention Analysis for Modeling and Forecasting Exchange Rates Rupiah Against Yen

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ABSTRACT

The Rupiah exchange rate against the Yen is one of the most important exchange rates in Indonesia since the agreement between the two countries to conduct investment and trade transactions using local currency. Exchange rate movements tended to strengthen during 2019. In 2020 there was a COVID-19 intervention and there was a significant weakening. An intervention is an event that causes a sharp increase or decrease in time series data. Intervention analysis is an analysis used on the data affected by the intervention by measuring the magnitude of the change in value and the duration of the intervention. Intervention analysis research on data on the rupiah exchange rate against the yen is still very rarely done. This study aims to apply intervention analysis in modeling and forecasting the Rupiah against the Yen exchange rate by considering the impact of the COVID-19 intervention. Research shows that the COVID-19 intervention on the Rupiah exchange rate against the Yen has had a long impact with the best intervention model being ARIMA (4,2,0) with an order of intervention (0,1,0). The level of forecasting accuracy using the model is very good with a MAPE value of 2.69%.

Keywords: ARIMA, Intervention Analysis, MAPE.

INTRODUCTION

The world was shocked by COVID-19 in Wuhan at the beginning of 2020. The COVID-19 virus attacked several countries so quickly that the World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020 (WHO, 2021). The COVID-19 pandemic has not only impacted the health sector but also the global economy. The International Monetary Fund (IMF) announced that world economic growth in 2020 experienced a contraction of 3.5%, which was lower than the 1998 Asian monetary crisis and the 2009 global financial crisis (Muhyiddin & Nugroho, 2021). Global financial markets moved erratically and caused a bearish Rupiah exchange rate from February to March 2020 (Bappenas, 2020).

Currency exchange is a country's currency that is translated into another country's currency (Nurmasari & Nur'aidawati, 2021). Important currency exchange for Indonesia is the Indonesian Rupiah (IDR) to Japanese Yen (JPY). This condition is because the Governor of Bank Indonesia and the Minister of Finance of Japan agreed to trade and investment transactions using local currency and this has been implemented since August 31, 2020(Bank Indonesia, 2021).

The Rupiah to Yen exchange was stable and experienced a strengthening of 2.29% in 2019, but temporarily. The

Rupiah has been bearish to the Yen since February 28 2020 due to public negative sentiment towards the increasing cases of COVID-19 and the pressure on the United States Dollar (USD) causing financial market players to sell shares and divert investment funds to options that are not affected by the global economic crisis, those are Yen currency (Pransuamitra, 2020).

Uncertain currency movements require forecasting to avoid losses, commonly known as time series data forecasting (Montgomery et al., 2008). Time series data forecasting is done by analyzing past data to predict future values. The method is Box-Jenkins with the Integrated Moving Average (ARIMA) model developed by George E.P. Box and Gwilym M. Jenkins in 1970 (Cryer & Chan, 2008). The ARIMA model was developed to work on non-stationary data and can be applied to all data patterns (Makridakis et al., 1997).

Forecasting the Rupiah to Yen exchange can use the ARIMA model, but there is the influence of the COVID-19 pandemic which results in forecasting sharp increases using data in the ARIMA model to be inaccurate (Wei, 2006). The study of time series data analysis shows that the bearish Rupiah to Yen exchange due to COVID-19 is known as an intervention. An intervention is an event that causes a strong increase or decrease in time series data.

The analysis that can be used to analyze time series data where there are events affecting the data pattern is intervention analysis. Intervention analysis is known as step function intervention and pulse function intervention. The step function intervention is an intervention that affects data over a long period of time, while the pulse function intervention is an intervention that affects a short time (Wei, 2006).

Many studies using intervention analysis have been carried out, namely Etuk's research (2017) on the Nigerian exchange rate (NGN) against the Yen exchange rate due to the economic recession in Nigeria (JPY) (Etuk et al., 2017) and Zukrianto's research (2021) which also using intervention analysis to predict the LQ45 Stock Index due to the COVID-19 pandemic (Zukrianto et al., 2021). Based on previous data and explanations, this study focuses on modeling and predicting the exchange rate of the Rupiah against the Yen with the COVID-19 intervention using intervention analysis.

METHOD

In the method section, it is explained about Stationarity, ARIMA Model, Parameter Significance Test, Selection of the Best Model, Residual Test, Intervention Model, and Forecasting Accuracy Level.

Data

The research uses daily data on the Rupiah to Yen exchange for the period January 2019 to October 2021. The data is obtained from the website https://id.investing.com/. The amount of data used is 717. The sample is divided into data for modeling (data training) and data for validation (data testing). Data for modeling is 586 samples and validation is 131 samples.

Stasionerity

The assumption of stationarity in the time-series analysis consists of stationarity in the mean and variance. The average stationary data show that the average fluctuates at a constant average, while the stationary data in the variance show that the constant variable value

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fluctuates over time (Makridakis et al., 1997). Data that are not stationary in variance are handled using a Box-Cox transformation, and data that are not average are handled by means of differentiation (Wei, 2006).

Check stationarity in variance can be seen in through the Box-Cox plot. Data that are stationary in variance have a lambda value (close to one or between the upper and lower bounds of a Box-Cox plot containing a value of one (Wei, 2006). Stationary in mean can be carried out through the Augmented Dickey Fuller (ADF) test with the hypothesis:
H_0: the data are not stationary in mean
H_1: the data are stationary in mean
The statistical test is a t-test (Box et al., 2015):

$$t_{hit} = \frac{\delta}{SE(\delta)}$$

The test criteria for the ADF test not received H_0 if $t_{hit} > t_{\frac{\alpha}{2},db}$.

Autocorrelation Functions (ACF)

Autocorrelation describes the relationship between the values of the observed variables (Makridakis et al., 1997). The autocorrelation function (ACF) can be used to view data stationarity and identify a provisional model for time series data. The formula for calculating ACF, is as follows (Wei, 2006):

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Z_t - \bar{Z})(Z_{t+k} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2}$$

where
$\hat{\rho}_k$: autocorrelation coefficient for a lag of k periods
Z_t: observation value at the time t
$\bar{Z}$: mean of the values of the series
Z_{t+k}: observation value at the $t + k$
n: total number of observations

Partial Autocorrelation Functions (PACF)

Partial autocorrelation is used to measure the degree of relationship between variable values Z_t and variable eliminating values Z_{t+k} after eliminating the effect of its dependence on $Z_{t+1}, Z_{t+2}, \dots, Z_{t+k-1}$ (Cryer & Chan, 2008). The formula for calculating PACF is as follows (Wei, 2006):

$$P_k = \frac{Cov[(Z_t - \hat{Z}_t), (Z_{t+k} - \hat{Z}_{t+k})]}{\sqrt{Var\,(Z_t - \hat{Z}_t)}\sqrt{Var(Z_{t+k} - \hat{Z}_{t+k})}}$$

where
P_k: partial autocorrelation coefficient for a lag of k periods
$\hat{Z}_t$: estimated value at the time t
$\hat{Z}_{t+k}$: estimated value at the time $t + k$

ARIMA Model

The ARIMA model uses past and present data from the dependent variable to predict future periods and does not use independent variables (Yunita, 2019). The model developed from AR, MA, and ARMA is used for stationary time series data, whereas the ARIMA model is used for non-stationary time series data; therefore, differentiation must be made to achieve stationarity. The differencing process is denoted so that the ARIMA model is denoted by ARIMA (p,d,q) (Wei, 2006):

$$\emptyset_p(B)(1 - B)^d Z_t = \theta_q(B)\, a_t$$

where
Z_t: observation value at the time t
a_t: residual value at the time t
$\emptyset_p$: autoregressive parameter
θ_q: moving average parameter
$(1 - B)^d$: process of differencing with orde-d
p: orde autoregressive
q: orde moving average
The pattern formed on the ACF and PACF plots for the ARIMA(p,d,q) model is shown in table 1.

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Table 1. Identification ARIMA Model based on ACF and PACF Plots

	ACF	PACF
AR(p)	Drop exponentially	Cut off after lag p
MA(q)	Cut off after lag ke-p	Drop exponentially
AR(p) atau MA(q)	Cut off after lag ke-p	Cut off after lag ke-q
ARMA(p,q)	Drop exponentially	Drop exponentially

Parameter Significance Test

The parameter significance test was carried out through the t-test. The hypothesis of the t-test, is as follows (Makridakis et al., 1997):

H_0: $\hat{\tau} = 0$ (Parameters suspected in the model are not significant)
H_1: $\hat{\tau} \neq 0$ (Parameters suspected in the model are significant)
The statistical test is written as follows:

$$t_{hit} = \frac{\hat{\tau}}{SE_{(\hat{\tau})}}$$

where
$\hat{\tau}$: estimated value of parameters
$SE(\hat{\tau})$: standard error of $\hat{\tau}$
n: total number of observations
The test criterion is to reject H_0 if $t_{hit} > t_{\frac{\alpha}{2},db}$.

Model Selection

The selection of the best model can also comparing the Mean Square Error (MSE), Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) values with the criteria for the best model being the model with the smallest MSE, AIC and BIC values. The calculation of the criterion value is as follows (Hanke & Winchern, 2014):

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2$$

$$AIC = \ln\hat{\sigma}^2 + \frac{2}{n}r$$

$$BIC = \ln\hat{\sigma}^2 + \frac{\ln(n)}{n}r$$

where
Z_t: observation value at the time t
$\hat{Z}_t$: estimated value at the time t
n: total number of observations
$\hat{\sigma}^2$: residual sum of squares divided by the number of observations
r: total number of parameters

Residual Assumptions Test

There are two assumptions that must exist, namely the assumption of white noise residuals and normally distributed residuals. The residual white noise assumption test is used to check whether the residuals from the model formed are not correlated with each other. Check assumptions using the Ljung-Box test with the hypothesis as follows (Wei, 2006):
H_0: there is no autocorrelation on lag $1,2,\dots,k$
H_1: there is autocorrelation on lag $1,2,\dots,k$
The statistical test is written as follows:

$$Q = n\,(n+2)\sum_{k=1}^{K}\frac{\hat{\rho}_k^2}{(n-k)}$$

where
n: total number of observations
K: sum of lags
k: lag difference
$\hat{\rho}_k$: autocorrelation coefficient for a lag of k periods
The test criterion is to reject H_0 if $Q > \chi^2_{\alpha;db}$.

Normal distribution assumption test is used to check that the residuals of the model are normally distributed. Examination of assumption using the Kolmogorov Smirnov test with the

hypothesis written as follows (Daniel, 1990):
H_0: Residuals are normally distributed
H_0: Residuals are not normally distributed
The statistical test is written as follows:

$$D = \mathrm{Sup}|\, S(x) - F_0(x)|$$

where
Sup: maximum value of $|\, S(x) - F_0(x)|$
S(x): Cumulative distribution function of the hypothesized distribution
$F_0(x)$: empirical distribution function of observed data
The test criterion is to reject H_0 if $D > D_{(\alpha,n)}$.

Intervention Analysis

Intervention analysis is a method for solving the effects of interventions on time series data. The purpose of the intervention analysis is to measure the impact of the intervention and predict the data affected by the intervention (Makridakis et al., 1997). Models for analysis the intervention is written as follows (Box et al., 2015):

$$Z_t = \frac{\omega_s(B)}{\delta_r(B)} B^b \xi_t + \frac{\theta_q(B)}{\emptyset_p(B)(1-B)^d} a_t$$

and

$$\omega_s(B) = \omega_0 - \omega_1 B - \cdots - \omega_s B^s$$
$$\delta_r(B) = 1 - \delta_1 B - \cdots - \delta_r B^r$$

where
Z_t: observation value at the time t
ξ_t: intervention variable at the time t
b: time delay of the intervention effect
s: time of influence of intervention since the period
r: data patterns after the period
a_t: residual at the time t
$\emptyset_p$: autoregressive parameter
θ_q: moving average parameter
$(1-B)^d$: process of differencing with orde-d
p: orde autoregressive
q: orde moving average

Forecasting Accuracy Rate

The level of accuracy of prediction results using the selected model can be solved by calculating the Mean Absolute Percentage Error (MAPE). The value calculation is as follows (Hanke & Winchern, 2014):

$$\mathrm{MAPE} = \left(\frac{100\%}{n}\right) \sum_{t=1}^{n} \frac{|Z_t - \hat{Z}_t|}{Z_t}$$

where
Z_t: observation value at the time t
$\hat{Z}_t$: estimated value at the time t
n: total number of observations

The MAPE value that has been obtained is then used to determine the level of forecasting ability of the model used as shown in table 2 (Chang et al., 2007).

Table 2. Accuracy Criteria of MAPE

MAPE Value	Forecasting
< 10%	Excellent
10% - 20%	Good
20% - 50%	Enough
> 50%	Inaccurate

Intervention Analysis Procedure

Research analysis using the procedure:
1. Exploring Rupiah to Yen exchange data using a time series plot.
2. Grouping all data into two parts, namely training and data testing.
3. Grouping the training data into two parts, namely data before and after the intervention occurred until the last data.
   a.The first part of the data starts from the first observation data (T=1) to data before the intervention (T=303), namely data from January 1 2019 to February 27 2020.
   b. The second part of the data starts from data before the intervention (T=304) to the last observation data

(T=586), namely data from 28 February 2020 to 23 April 2021.

4. Create an ARIMA model before the intervention using the training data in part one.
   a. Test the stationarity of the mean and variance of time series data.
   b. Identification of the provisional model by observing the ACF plot and PACF plot.
   c. Estimate the parameters in the provisional model.
   d. Perform a significance test on the parameters of the intervention model
   e. Determine the best model by paying attention to the smallest MSE, AIC, and BIC values.
   f. Test the assumption of residual white noise and test the assumption of normal distribution on the best model.
   g. Prediction using the best model.

5. Define the Intervention model using the training data in part two.
   a. Calculate the residual value obtained by the difference between the forecasting results of the ARIMA model before the intervention and the actual data in the second part.
   b. Identify the order value (b, r, s) by looking at the residual graph. The order b response states the time the intervention began to occur, the orders states the length of time the intervention effect has occurred since period b, and the order r states the data pattern that was formed after the b+s period.
   c. Estimate the parameters in the intervention model.
   d. Check the significance of the parameters of the intervention model.
   e. Determine the best intervention model.
   f. Test the assumption of white noise residuals and test the assumptions of normally distributed residuals in the intervention model.
   g. Prediction of Rupiah to Yen exchange using selected intervention models.

5. Measure the accuracy of the forecasting results of the selected intervention model by calculating the MAPE value using test data and forecasting data from the intervention model.

RESULT AND DISCUSSION

Data intervention began on February 28 2020 due to negative sentiment from the public's response to the increasing number of COVID-19 cases and pressure on the dollar (USD) which had the effect of a massive sell-off of stocks. This situation has an impact on the global stock market economy. The Yen currency experienced a sharp appreciation which caused the currencies of a number of countries to be significantly bearish to Yen currency, including the rupiah (Pransuamitra, 2020).

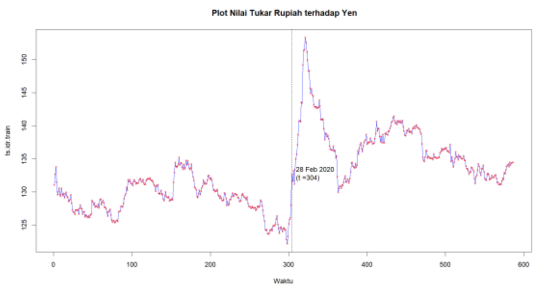

Figure 1. Plot of the Rupiah Exchange to Yen for the period January 1, 2019 - April 23, 2021

Stationarity

Box Cox plot in figure 2 shows that the lambda value (λ) is 1,7491 > 1 so there is no need to transform because it is already stationary for the variance, while the results of the Augmented Dickey Fuller test in table 3 show a p-value of 0,4195 > 0,05 so there is not enough evidence to reject H_0 which means the data are not stationary with respect to the average.

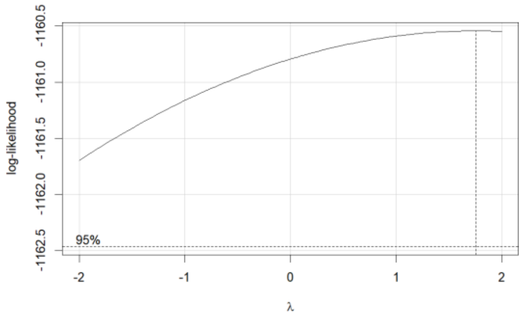

Figure 2. Box-Cox Plot Before Intervention

The results of the ADF test in table 3 show a p-value 0,01 < 0,05 than so reject H_0 which means that the data is stationary with respect to the average, but there is no significant lag so it cannot be used to identify the model. The results ADF of the test for the 2nd differencing also show that the data are stationary with respect to the average, so that it can be used to identify the ARIMA model.

Table 3. ADF Test

ADF Test	p-value
Before differencing	0,4195
First Differencing	0,01
Second Differencing	0,01

ARIMA Model

Stationary data with variance and mean can be used to identify a temporary ARIMA model through the ACF and PACF plots shown in Figure 3 and Figure 4. The data before the 2nd differencing intervention on the ACF and PACF plots shows a significant lag so that it can be used to identify the model. The patterns on the two plots form a cut-off pattern so that the model obtained is ARIMA(1,2,0), ARIMA(2,2,0), ARIMA(3,2,0), ARIMA (4,2,0), and ARIMA(0,2,1).

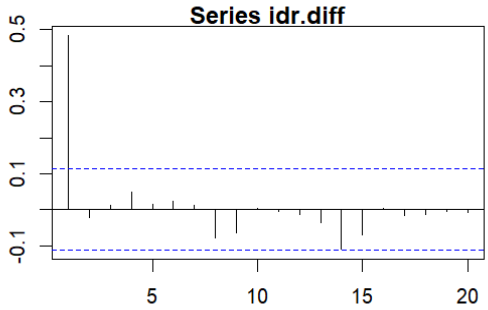

Figure 3. Plot of ACF Data before the second Differentencing Intervention

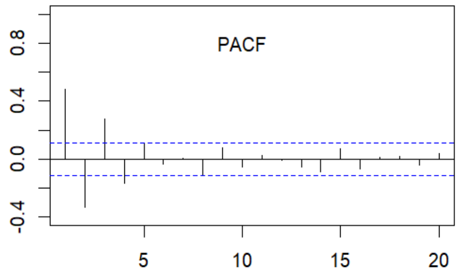

Figure 4. PACF Plot Data Before the second Differentencing Intervention

Parameter Significance Test for ARIMA Model

The model that can be used for the next process is a model where all parameter values are significant. The estimated value and significance test of parameters can be seen in table 4. The result is that all temporary ARIMA models have significant parameter values because the p-value < 0.05 so that they can be used for further processing.

Table 4. Estimation and Test of Parameters

Model	Parameter	p-value
ARI (1,2)	$\emptyset_1$ =-0,412	2,220e^{-15}
ARI (2,2)	$\emptyset_1$ = -0,572 $\emptyset_2$ = -0,361	0 1,718e^{-10}
ARI (3,2)	$\emptyset_1$ = -0,685 $\emptyset_2$ = -0,559 $\emptyset_3$ = -0,328	0 0 1,518e^{-8}
ARI (4,2)	$\emptyset_1$ = -0,739 $\emptyset_2$ = -0,652 $\emptyset_3$ = -0,461 $\emptyset_4$ = -0,189	0 0 7,702e^{-11} 1,613e^{-3}
IMA (2,1)	θ_1 = -0,999	0

Model Selection

The results of the temporary model criteria values are shown in table 5. The result is the best model is the ARIMA model (0,2,1) so that the model used next is the ARIMA model (0,2, 1), but this model does not match the residual assumptions when forming the intervention model so that the model used next is the ARIMA model (4,2,0) where the model has the second smallest MSE, AIC, and BIC values.

Table 5. MSE, AIC, and BIC Values

Model	MSE	AIC	BIC
ARI (1,2)	0,557	684,58	691,99
ARI (2,2)	0,490	648,42	659,54
ARI (3,2)	0,443	620,06	634,89
ARI (4,2)	0,428	612,28	630,82
IMA (2,1)	0,379	573,86	581,27

Residual Assumptions Test for ARIMA Model

The Ljung-Box test results in table 6 for the ISPA model (4.2) show a p-value of 0.9908 > 0.05 so there is not enough evidence to reject H_0, which means the model matches the assumption of residual white noise, while the Kolmogorov- Smirnov shows a p-value of 0.4335 > 0.05 so it is impossible to reject H_0, which means that the model matches the assumption that the residuals are normally distributed.

Table 6. Residual Assumptions Test for Model ARIMA (4,2,0)

Residual Assumptions	p-value
Ljung-Box	0,9908
Kolmogorov-Smirnov	0,4335

Intervention Model

The order of intervention is identified through the residual response graph which is obtained by calculating the residual value between the actual data after the intervention and the ARIMA model forecasting data (4,2,0). The residual response graph can be seen in Figure 5.

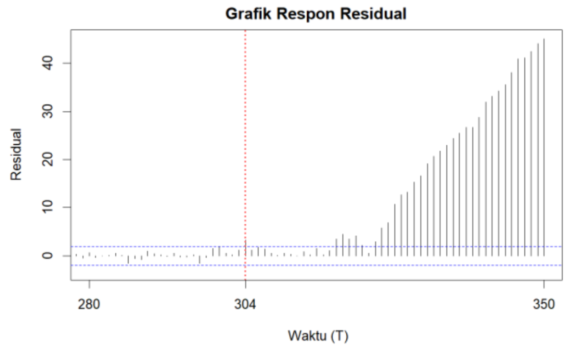

Figure 5. Residual Response

The pattern formed in Figure 5 is a gradual permanent pattern and has a long period of time so that the intervention function used is a step function. The significant limit on the residual response graph is or equal to 3 (0,6559) = 1,9677, the lag that comes out the first time is the lag at the intervention point (T = 304) so that order b = 0, the length of time the intervention affects the data until it returns to decline is s = 0,1 and the pattern of the residuals forms an exponential pattern so that order r = 1. The temporary intervention model formed is the ARIMA model (4,2,0) with an order of intervention (0,1,0) and an order of intervention (0,1,1).

Parameter Significance Test for Intervention Model

The results in table 7 show that the parameter estimates in the ARIMA model (4,2,0) with an intervention order (0,1,0) have a p-value < 0,05 so that all parameters are significant, whereas in the ARIMA model (4,2,0) with an order of intervention (0,1,1) there is one parameter with a p-value > 0,05 so that the parameter is not significant. Based on these results, the intervention model that can be used for the next process is the

ARIMA step function intervention model (4,2,0) with order (0,1,0).

Table 7. Estimation and Test of Parameters

Model	Parameter	p-value
ARIMA (4,2,0) Intervention order (0,1,0)	$\emptyset_1$ = -0,742	< 2,2e^{-16}
	$\emptyset_2$ = -0,569	< 2,2e^{-16}
	$\emptyset_3$ = -0,232	1,864e^{-14}
	$\emptyset_4$ = -0,232	1,635e^{-08}
	ω_0 = 1,936	1,199e^{-05}
	δ_1 = -0,570	6,351e^{-06}
ARIMA (4,2,0) Intervention order (0,1,1)	$\emptyset_1$ = -0,745	< 2,2e^{-16}
	$\emptyset_2$ = -0,332	9,175e^{-09}
	$\emptyset_3$ = -0,118	0,034
	$\emptyset_4$ = -0,089	0,046
	ω_0 = 4,432	0,004
	ω_1 = -2,18	0,134
	δ_1 = 1,006	< 2,2e^{-16}

Residual Assumptions Test for Intervention Model

The Ljung-Box test results in table 8 for the ARIMA model (4,2,0) with intervention order (0,1,0) show that the p-value is 0,7351 > 0.05 so there not match to reject H_0, which means that the model meets the assumption of residual white noise, while the Kolmogorov-Smirnov test results show a p-value of 0,0602 > 0,05 so there is not match to reject H_0 which means that the model meets the assumption of normally distributed residuals. The ARIMA model (4,2,0) with an intervention order (0,1,0) has match all the residual assumptions so that the model is feasible to use in forecasting.

Table 8. Residual Assumptions Test for Intervention Model

Residual Assumptions	p-value
Ljung-Box	0,7351
Kolmogorov-Smirnov	0,0602

Accuracy of Forecasting

The overall forecasting results can be seen in Figure 6. The pattern formed on the plot shows that the Rupiah exchange to Yen moves quite fluctuating with values ranging from 121,63 to 137,70. The average forecasting value is 132.52 with the smallest value occurring on October 25, 2021 and the largest value occurring on June 4, 2021.

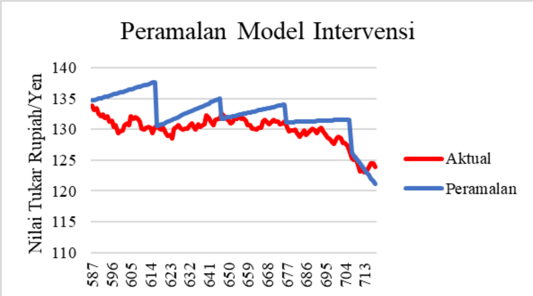

Figure 6. Intervention Model Forecasting

The accuracy of the step function intervention model (4,2,0) with the order of intervention (0,1,0) is measured by calculating the MAPE value shown in table 9. The MAPE value for forecasting results is 2,69%, which means the model is very good for use in forecasting because it has a MAPE value of <10%.

Table 9. Forecasting Accuracy Rate of Intervention Model

	MAPE Value
Testing Data	2,69%

CONCLUSION

The intervention model selected for forecasting is the ARIMA model (4,2,0) with an order of intervention (0,1,0). Forecasting results using this model for the period April 26, 2021, to October 25, 2021, tended to fluctuate with values ranging from 121,63 137,70. The level of accuracy of the forecasting results has a MAPE value of 2,69% so the model can be said to be very good in forecasting. Suggestions for further research include conducting multi-input intervention analysis research by considering several economic factors to obtain a more accurate forecasting model.

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