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ARIMA Model for Forecasting COVID-19 Positivity Rate in Jakarta

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Abstract

COVID-19, a global pandemic since early 2020, has affected numerous countries worldwide, including Indonesia. The positivity rate serves as a crucial metric for gauging the extent of COVID-19 transmission in a specific region. The surge in COVID-19 cases in Jakarta has notably impacted various industries, particularly the healthcare sector. In this paper, ARIMA model is used to predict the number of daily COVID-19 cases in Jakarta. The optimal model for predicting the positivity rate over the next 10 days, from June 22, 2022, to July 1, 2022, is identified as ARIMA (1,1,3). The forecasting error is quantified by the MAE of 0.5625, MSE of 0.0161, RMSE of 0.1268, and MAPE of 0.68% all of which attest to its high accuracy. From a mathematical perspective, the outcomes of this study offer advantages by elucidating the utilization of the ARIMA technique for forecasting time series data, particularly in scenarios involving disease spread, necessitating meticulous management. Additionally, within the healthcare domain, these findings offer valuable insights into endeavors aimed at controlling infectious diseases, particularly COVID-19, should similar outbreaks occur in the future.

Keywords: ARIMA; COVID-19; Forecasting; Time Series Analysis

I. Introduction

The onset of the Corona Virus Disease 2019 (COVID-19) pandemic occurred in Wuhan, China, in December 2019, and subsequently, it has disseminated to a majority of the globe. The COVID-19, a new and highly infectious virus from the Coronaviridae family, is suspected to have been transmitted to humans from animals [1]. Given that Indonesia ranks as the fourth most populous nation worldwide, it is anticipated that the COVID-19 pandemic will exert a notable adverse effect and persist for a longer compared to less populous countries [2]. The highest daily cases in Indonesia in 2022 occurred on February 9, 2022, reaching 46,843 new cases in just one day [3]. The positivity rate 18.59% on February 19, 2022. According to the World Health Organization (WHO) regarding the conditions of transmission of COVID-19, sets the standard for the positivity rate at 5% [1]. There was no COVID-19 vaccination or treatment available in Indonesia until the end of 2020. It would not be incorrect to describe this illness as the "enemy of humanity" given that it is currently causing a serious health crisis on a global scale. The only thing we can do in this situation is try to stop infections from happening and get our healthcare system ready for whatever the future may hold. Therefore, in order for models to assist policy makers, medical professionals, and the general public, it is imperative that they be realistic and computationally

competent. Medical systems can get ready for new patients by modeling the illness and offering projections of potential future positive rates.

Numerous mathematicians or statisticians investigate the dynamics of COVID-19 transmission by employing mathematical modeling or statistical techniques for prediction. Alkahtani et al. [4] and Tuan et al. [5] utilized fractional derivatives in their respective models, with [4] concentrating on the virus spread in Italy and [5] presenting a global transmission model. Both studies examined the stability and numerical aspects of their models. Alkahtani [6] extended this research by integrating an asymptomatic category into the model, while Inayah [7] devised a model grounded on the SEIR model, which incorporated two-phase vaccination, symptomatic and asymptomatic individuals, and quarantine measures. J. Tsetimi et al. [8] employed a deterministic SEIR model to explore the dynamics of COVID-19 transmission. Their mathematical analysis covered various aspects such as positivity and solution constraints, equilibrium points, basic reproduction number, stability assessment, and sensitivity analysis. Additionally, they conducted numerical simulations to examine how sensitive parameters affect the basic reproduction number. Furthermore, a variety of time series models have been utilized to assess the propagation of COVID-19. For instance, Khennou [9] employed both univariate and multivariate time series models, incorporating ensemble techniques based on LSTM and GRU, to forecast new cases in Canada. Harvey et al. [10] devised a bivariate model to monitor the outbreak in the UK, by contrasting growth rates and reproductive numbers. Their research involved the use of a novel time series model inspired by econometrics to monitor the outbreak and predict crucial indicators. This entailed fitting trends using the logarithm of the growth rate of new cases, employing a multivariate state space model to amalgamate information from multiple data sources, utilizing a Kalman Filter model to refine the current state and disseminate forecasts, and evaluating forecast accuracy using Mean Absolute Percentage Error (MAPE) over a 14-day timeframe. The use of MAPE allows for a consistent measurement of forecast accuracy applied to two different types of data, regardless of the time difference in data availability. Dhivya et al. [11] utilized the Prophet forecasting model to project the future spread of active cases in India, with a specific focus on the second wave of data spanning the last four months. Radwan [12] implemented a time series regression model to estimate the number of confirmed cases across 62 countries, resulting in a notable decrease in error. Their approach encompassed building a forecasting model employing seven regression models, feature engineering techniques, and evaluating performance using Long Short Term Memory (RMSLE). The findings of these studies demonstrate the efficacy of eXtreem Gradient Boosting (XGB) and Light Gradient Boosting Machine (LGBM) models.

The statistical prediction models are one of the tool useful both in forecasting and controlling the global epidemic threat. Some researchers have conducted the research using Autoregressive Integrated Moving Average (ARIMA). Jain et al. [13] presented a time-series forecasting model to predict upcoming cases. This study use data from COVID-19 cases in India that occurs from 30th January 2020 to 23rd December 2020. In term of Root Mean Squared Error (RSME), the result of this study shows that the ARIMA (8,2,1) model performed best among all models. Singh et al. [14] used ARIMA to predict daily cases in Malaysia. This research utilizes the daily confirmed COVID-19 cases in Malaysia recorded from January 22 to March 31, 2020, for analysis, while data spanning April 1 to April 17, 2020, is reserved for validation purposes. The results of this study indicate that the ARIMA (0,1,0) model demonstrated the closest fit to the observed data, yielding a MAPE value of 16.01 and a Bayes Information Criteria (BIC) value of 4.170. The forecasted trajectory of COVID-19 cases indicates a declining trend until May 1, 2020. The same predicted daily cases of COVID-19 used the ARIMA model was also studied in Italy, Spain, and Turkey [15]. Utilizing data from the European Centre for Disease Prevention and Control, this study applied the ARIMA model to forecast the number of COVID-19 cases and deaths. This study uses the daily case and death data of COVID-19 in Italy, Spain, and Turkey from February 2, 2020 to March 27, 2020. According to the study's findings, there should be a decline in cases in Italy and Spain by July and a decline in cases in Turkey by September.

Other studies constructed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict confirm case, recovery case, and deceased cases for the next 30 days [16]. The data used in this work was taken from the Indian government from January 30, 2020, until June 30, 2020. The result

show that ARIMA (8,2,1) is the best model with an accuracy 99.7 % in confirm cases, 99.15% in recovery cases, 99.08 % in deceased cases. Duangchaemkarn et al. predicting confirmed cases of COVID-19 using the SARIMA model for 7 days, 14 days, and 28 days [16]. They used COVID-19 data that occurred in Thailand from December 1, 2021, to April 30, 2022. The results show that the average of MAPE for predicting COVID-19 daily confirmed cases for the next 17 days, 14 days and 28 days were 17.69%, 24.30%, and 55.08%, respectively. The average MAPE for predicting COVID-19 daily death for next 7 days, 14 days, and 28 days were 6.35%, 5.81%, and 5.82%, respectively. The average MAPE for predicting COVID-19 daily recovery cases for the next 7 days, 14 days and 28 days were 10.27%, 15.40%, and 28.41%, respectively. Hariadi applied the ARIMA model to forecast cases in Jember Regency [17]. The approach utilized to predict further COVID-19 positive cases in Jember Regency involved employing the ARIMA model. This research was carried out within Jember Regency, East Java, utilizing secondary data acquired from March 28, 2020, to January 30, 2021. The analysis applied the ARIMA model to the time series data concerning the weekly increment of COVID-19-positive cases. The key discoveries presented include employing the ARIMA model for forecasting COVID-19 occurrences in Jember Regency, identifying a professional ARIMA (1,2,3) model, and offering predictions for future cases.

Based on the background above, this study puts the novelty that lies in the application of the ARIMA model to forecast the positivity rate of COVID-19 in Jakarta, Indonesia, using the latest data taken from January 2022 until May 2022 [3]. This study identified the best ARIMA model and then predicted the positivity rate for the next 10 days. This study is different from previous studies that aim to predict the number of cases. This study emphasizes the positivity rate which is an important indicator to understand the level of transmission and the adequacy of testing.

II. Literature Review

The positivity rate is the percentage of positive people out of all people tested or in other words the number of confirmed cases in a day divided by the number of people tested for diagnosis. When the positivity rate is low, it indicates that only a small percentage of those who are tested are positive, leading to the conclusion that the risk of transmission in the community tends to be small. On the other hand, a high positivity rate indicates that a high percentage of those who were tested are positive, which leads to the conclusion that there is a high risk of transmission in the population. During 2.5 years, Indonesia has experienced the highest level of positivity rate in 2020 on 29/03/2020 it reached 56.7%. In 2021 on 03/07/2021 it reached 51.7%. Then in half of 2022 on 11/02/2022 the positivity rate reached 40.1% [1].

The next discussion is a summary of ARIMA which refers to Cryer and Chan [18]. By examining specific patterns in the data, time series analysis is a technique for extracting information from the data and predicting the output data. One must be mindful of both stationary and non-stationary data when analyzing data. If the variance around the mean remains consistent over a specific time frame and the data pattern centers around a fixed average value, it is classified as stationary. However, the majority of data encountered is non-stationary, necessitating initial transformation into a stationary format before undergoing further analysis. Time series data can be utilized in a statistical analysis model known as autoregressive integrated moving average (ARIMA). These models are utilized to predict data trends based on historical data. Stationarity testing is the primary step once the data is available, requiring transformation into a stationary format if it is not already. Differencing is one technique used to achieve this transformation. Subtracting the previous observation from the current observation is how this is accomplished. The next step involved finding out autocorrelation and partial auto-correlation between the values of the data lag time k or Y_t and Y_{t-k}. The notation of autocovariance and autocorrelation are $\gamma_k$and ρ_k, respectively, where $k = \pm 1, \pm 2, \pm 3, \ldots$ The general formula of autocovariance as follows,

$$\gamma_k = Cov\,(Y_t, Y_{t-k}). \tag{1}$$

For the autocorrelation as follows,

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https://idjams.com/index.php/jms/index

$$\rho_k = \frac{Cov\ (Y_t, Y_{t-k})}{\sqrt{Var(Y_t).Var(Y_{t-k})}} = \frac{\gamma_k}{\gamma_0}. \tag{2}$$

If Y_t is a time series process with a normal distribution, then the partial auto-correlation function can be written as follows,

$$\Phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \Phi_{k-1,j}\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \Phi_{k-1,j}\rho_j}, \tag{3}$$

where $\Phi_{k,j} = \Phi_{k-1,j} - \Phi_{kk}\Phi_{k-1,k-j}$, for $j = 1, 2, \dots, k-1$.

The Autoregressive model is a model that works with the concept of lag which is defined as forecasting a data series based on past data in the series. The general formula for the autoregressive model as follows,

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t, \tag{4}$$

where Y_t represent the variable value at time t, ϕ_i represent the autoregressive coefficient, $e_t$represent the error at time t, and p represent the autoregressive order. The moving average is a model of time series values that works based on elements of error in current and past data. The general formula of the moving average is as follows,

$$Y_t = e_t - \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q}, \tag{5}$$

where Y_t represent the variable value at time t, θ_i represent the moving average coefficient, et represent the error at time t, and q represent the moving average order. Combining the autoregressive and moving average models results in the ARMA model. This model can be expressed by following the formula,

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}. \tag{6}$$

The ARMA model is expanded upon by the ARIMA model, which requires that the data be transformed into stationary data before being utilized in the differencing process that results in model analysis. ARIMA has 3 parameters, namely (p, d, q) where p is the autoregressive degree, d is the differencing degree and q is the moving average degree. If the differencing process is denoted by $W_t = \nabla^d Y_t$where $\nabla Y_t = Y_t - Y_{t-1}$ and yield stationary data. Thus, W_t can be written in the form of the ARMA model,

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \cdots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \dots - \theta_q e_{t-q}. \tag{7}$$

For the first order of differencing, $d = 1$, will give ARIMA $(p, 1, q)$ has model equation as follow,

$$Y_t = \psi_1 Y_{t-1} + \psi_2 Y_{t-2} + \cdots + \psi_p Y_{t-p} + \psi_{p+1} Y_{t-p-1} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}. \tag{8}$$

III. Methods

The discussion here is still presentation from Cryer and Chan [18] and use the level of significance by 0.05. Forecasting in this study uses the Box-Jenkins method or what is often called the ARIMA model. The results obtained are recommendations for the best ARIMA model from several prospective models. The following is an explanation of the steps how to use the Box-Jenkins method. The first step is data preparation for the analysis to obtain the ARIMA model. In the next step, the data will be tested

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https://idjams.com/index.php/jms/index

to check the stationary data using the Augmented Dickey-Fuller (ADF) test. The data shows stationary if the resulting p-value is lower than 0.05. In case the data is non-stationary, we can do differencing data one or more times such that the data become stationary.

The next step is present the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot to determine the model specification. By looking at the ACF and PACF plot, p is the cut point for PACF and q is the cut point for ACF. Then, after the value p, d, q is obtained, the next step is the diagnostic check of normality and correlation of the residual. The model is said to be accepted if its residual is normally distributed and there is no correlation. To test the normality of the residuals, a test can be used, such as qqplots and Shapiro test. Ljung Box test is used to check the correlation of residual. The last step is to predict the value of the positivity rate for the next 10 days using the best model. The summary of this method is illustrated in Figure 1.

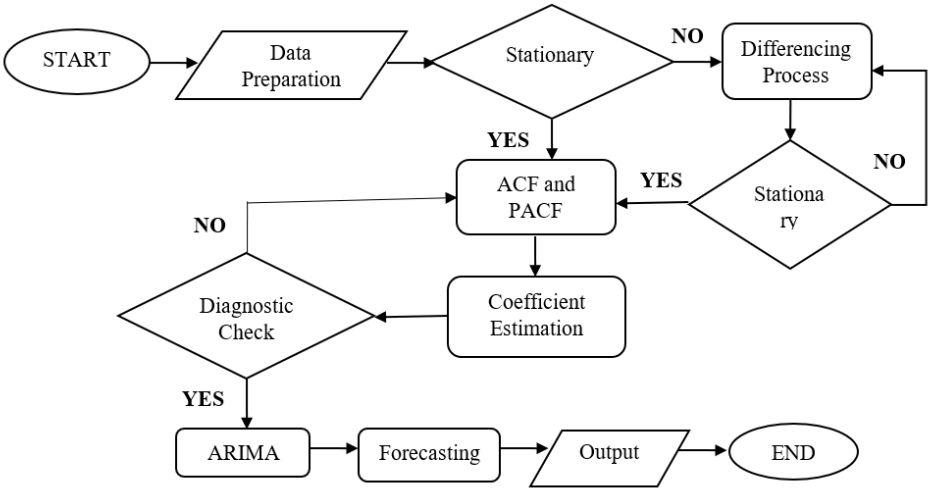

Figure 1. Summary of Steps in Box-Jenkins Method

IV. Result and Discussion

The data that we used is positivity rate Covid-19 in Jakarta from January 1, 2022 until June 21, 2022 obtained from official website of Satgas Covid-19 DKI Jakarta [3]. All calculations, tests and graphing are done with the help of R software.

Table 1. Statistical Descriptive of Positivity Rate

Type	Value
Min	-0.004103
1st Qu	0.882619
Median	1.619288
Mean	1.643801
3rd Qu	2.420423
Max	3.265673

The summary of statistical descriptive of the data can be seen on Table 1. The mean value that is not much different from the median value indicates that the data has a distribution that is close to symmetrical, so based on this assumption it can be said that the data is normally distributed. The positivity rate has minimum value -0.004 happened on Mei 18, 2022 and has maximum value is 3.27 happened on February 5, 2022. Hence the range is 3.274.

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Volume 2 Issue 1 June, 2025, pp. 1-10
https://idjams.com/index.php/jms/index

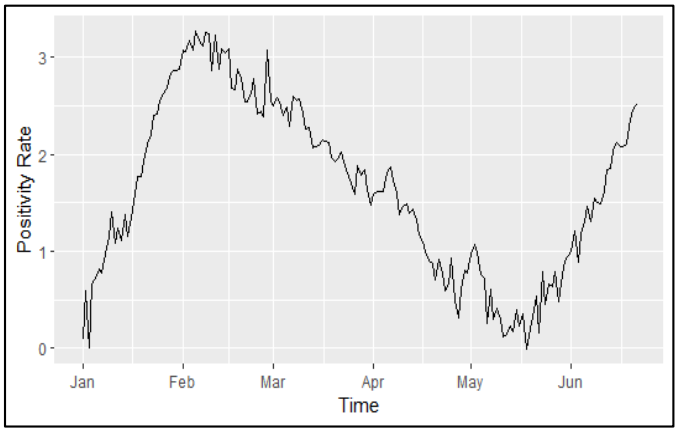

Figure 2. Plot Data of Positivity Rate January-June 2022

Figure 2 presents a plot of the positive rate from January to June 2022. This shows that there is a positive rate fluctuation but the trend is like sinusoidal. The date show first up to date February 5 then down until May 18, 2022. Last up again. After prepare the data, the ADF test is used to determine whether or not the data is stationary after the data has been prepared. According to the ADF test results, the data is not stationary, as indicated by the p-value of 0.82, which is greater than 0.05. Then, we must have the differencing step. The data after first differencing is shown in Figure 3 and the ADF test give us p-value by 0.02.

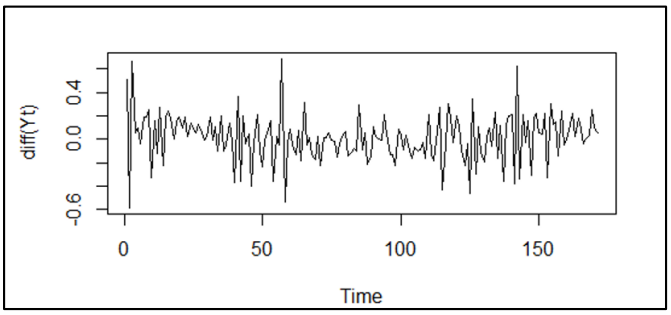

Figure 3. Plot Data after Differencing

After the second Differencing process, the p-value is less than 0.05 which means that the data is stationary and ready to be used. Orders of AR and MA can be determined using PACF for order p and ACF for order q. According to the cut off for PACF and ACF are both at lag 3 with the first differencing which give the $p = 1$, $q = 2$. Parsimony principle suggest the candidate modes are ARIMA (1,1,2), ARIMA (1,1,1), ARIMA (1,1,0), ARIMA (0,1,2), and ARIMA (0,1,1).

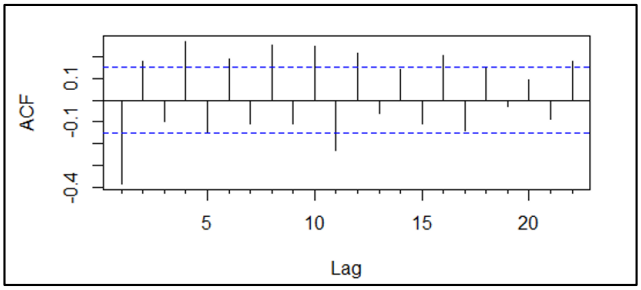

Figure 4. ACF Plot after Differencing Process

Indonesian Journal of Applied Mathematics and Statistics (IdJAMS)
ISSN 3064-4062
Volume 2 Issue 1 June, 2025, pp. 1-10
https://idjams.com/index.php/jms/index

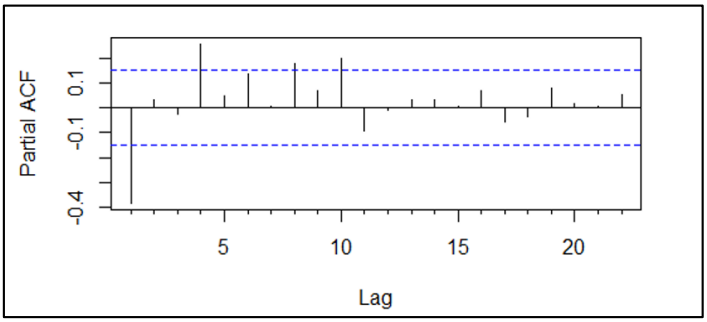

Figure 5. PACF after Differencing Process

Table 2. Parameter Estimation of ARIMA Model

ARIMA Model	AR1	MA1	MA2	Log Likelihood	AIC
ARIMA (1,1,2)	-0.9810	0.6915	-0.1888	47.59	-87.19
ARIMA (1,1,1)	-0.9681	0.8312	-	44.41	-82.83
ARIMA (1,1,0)	-0.3892	-	-	42.19	-80.39
ARIMA (0,1,2)	-	-0.3963	0.1719	42.43	-78.87
ARIMA (0,1,1)	-	-0.3074	-	39.3	-74.60

The next step is residual analysis to find the best candidate model. In this analysis, Saphiro test and Ljung-Box test is used for checking the normality and the exist of autocorrelation in residual, respectively. The p-value for the both of the test is presented at Table 3.

Table 3. ARIMA Residual Analysis

ARIMA Model	Saphiro Test	Ljung-Box Test
ARIMA (1,1,2)	0.8103	0.9168
ARIMA (1,1,1)	0.6726	0.0405
ARIMA (1,1,0)	0.2115	0.7806
ARIMA (0,1,2)	0.5564	0.8823
ARIMA (0,1,1)	0.0980	0.3439

According Table 3, Saphiro test dan Ljung-Box test give all p-value are larger than 0.05 unless ARIMA (1,1,1). Therefore ARIMA (1,1,2), ARIMA (1,1,0) ARIMA (0,1,2), and ARIMA (0,1,1) are passed for the both of the test. To determine the best model, we choose the mode with the lowest of AIC value. Then, according to AIC value presented at Table 2, we select ARIMA (1,1,2) as the best model.

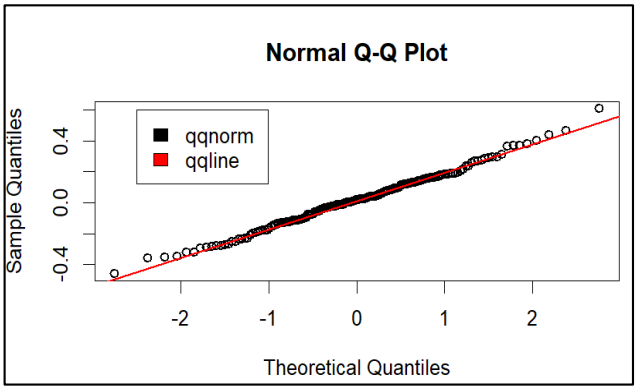

Figure 6. Normal QQ Plot

Indonesian Journal of Applied Mathematics and Statistics (IdJAMS)
ISSN 3064-4062
Volume 2 Issue 1 June, 2025, pp. 1-10
https://idjams.com/index.php/jms/index

Figure 6 confirm the result of Saphiro test for ARIMA (1,1,2) for the normality of the residual. The point seems to follow the straight line fairly closely, then we can assume this normality is fulfilled. By looking at Table 2, only model ARIMA (1,1,2) that pass Saphiro and Ljung-Box test. It follows that this model is selected as best model. The model of equation for ARIMA (1,1,2) is

$$Y_t = 0.019Y_{t-1} + 0.9810Y_{t-2} + 0.6915e_{t-1} + 0.6915e_{t-2} + e_t. \quad (9)$$

The plot of forecasting data with model ARIMA (1,1,2) for ten days from June 22, 2022 to 1 July 2022 is presented at Figure 7. The black line for the actual data and the blue line for the forecast data, and the grey area indicates the area of 95% confidence level.

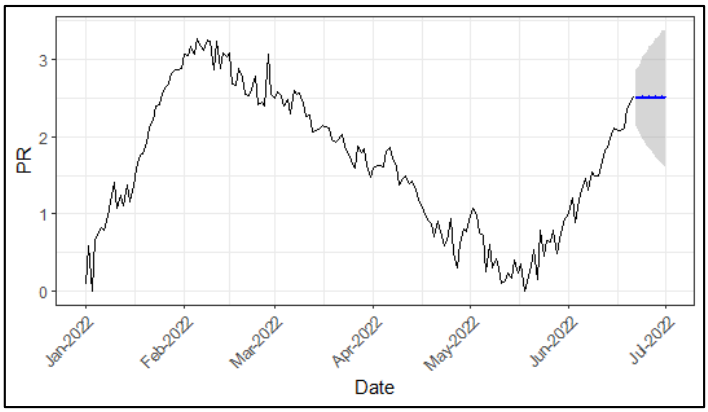

Figure 7. Forecasting Plot ARIMA (1,1,2)

Table 4 show the comparison of forecast data with actual data from ARIMA (1,1,2) which contain 10 actual observations. To discuss accuracy of the forecasting result, we run calculation to compute the error of forecasting as shown at Table 5. In this table y represent the actual observation and ŷ represent the prediction value from ARIMA (1,1,2). By using the results from Table 5, the further calculation gives us the forecasting error measurement as follows Mean Squared Error (MSE) of 0.0161, Root Mean Squared Error (RMSE) of 0.1268, Mean Absolute Error (MAE) of 0.5625, and MAPE of 0.68%. Since the Mean Absolute Percentage Error (MAPE) value here is less than 10%, then this forecasting of the positivity rate is said highly accurate [19].

Table 4. The Comparison of Actual and Forecast Data

Date	Actual Data	Prediction Data	Lower Bound	Upper Bound
22/06/2022	2.42560001	2.514645	2.153176	2.876113
23/06/2022	2.43363705	2.493773	2.050350	2.937197
24/06/2022	2.44874545	2.514247	1.983747	3.044748
25/06/2022	2.55799728	2.494163	1.904475	3.083851
26/06/2022	2.61948871	2.513865	1.856472	3.171258
27/06/2022	2.55176466	2.494538	1.788286	3.200790
28/06/2022	2.25926886	2.513497	1.750041	3.276954
29/06/2022	2.36556308	2.494899	1.688794	3.301004
30/06/2022	2.35646546	2.513143	1.656677	3.369610
01/07/2022	2.35179243	2.495246	1.600385	3.390107

It should be emphasized here that there is a limitation study, namely the results of forecasting are only based on the available data. If the data is added then there is a possibility that the accuracy of the forecasting results will change as well.

Table 5. The Error of Model ARIMA (3,2,3)

Time	$\lvert \hat{y} - y \rvert$	$(\hat{y}-y)^2$	$\frac{(\hat{y}-y)^2}{y}$
6/22/2022	0.089	0.0079	0.0032
6/23/2022	0.0601	0.0036	0.0015
6/24/2022	0.0655	0.0043	0.0018
6/25/2022	0.0638	0.0041	0.0016
6/26/2022	0.1056	0.0112	0.0043
6/27/2022	0.0572	0.0033	0.0013
6/28/2022	0.2542	0.0646	0.0286
6/29/2022	0.1293	0.0167	0.0071
6/30/2022	0.1567	0.0245	0.0104
7/1/2022	0.1435	0.0206	0.0086

V. Conclusion

In this work, we have applied ARIMA model to forecast positivity rate in Jakarta for ten days from June 22, 2022 to July 1, 2022. The result of residual analysis indicates that the best model is ARIMA (1,1,2) which the forecasting result is highly accurate at 95% confidence level. The model equation of ARIMA (1,1,2) is given by

$$Y_t = 0.019Y_{t-1} + 0.9810Y_{t-2} + 0.6915e_{t-1} + 0.6915e_{t-2} + e_t. \quad (10)$$

This research contributes to the application of the ARIMA method in its aim to forecast the COVID-19 Positivity Rate in Jakarta. The results of this study are expected to be applied in the field by relevant agencies such as the Ministry of Health. We believe that the positive rate forecasting results using the ARIMA model can be taken into consideration in policy making for COVID-19 control.

One of the weaknesses of ARIMA is that it cannot work well for long term forecasting. A longer forecasting period leads to an increase in prediction error, which reduces the long-term accuracy. This limits the practical application of the model to short-term planning only. To overcome this, in future research, we will try to implement deep learning approach, especially the LSTM algorithm. In addition, identifying the influence of external variables such as mobility trends or vaccination rates can improve forecast performance and provide deeper insights into the research.

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