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FORECASTING OF COVID-19 DAILY CASES IN INDONESIA USING ARIMA MODEL

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ABSTRACT

Keywords:
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COVID-19 (Coronavirus Disease 2019) continues to be a global issue. The disease began to spread due to direct contact with the seafood market in Wuhan, Hubei Province, China. COVID-19 cases globally and especially in Indonesia, are still increasing as well. Therefore, it is important to forecast future cases as a form of vigilance and materials to formulate strategies in controlling the spread and procurement of health systems. This study aims to predict daily cases of COVID-19 in Indonesia. This research includes non-reactive studies by collecting daily case data on COVID-19 from October 1st to December 31st, 2020 from the COVID-19 Task Force website in Indonesia. The results showed that the model that is fit to describe COVID-19 cases in Indonesia is ARIMA [5,1,0] with a model significance of 0.000 and constant of 0.049 (p value <0.05), Ljung-Box Q of 0.880 (p value >0.05) and residual normality of 0.330 (p value >0.05). The three months forecasting (from January to March 2021) showed a number that tended to increase. The increase in cases occurred due to environment, behavior, health services, and genetics. Therefore, it is necessary to increase cooperation between the government and the community so that efforts to suppress the growth of COVID-19 cases are optimal.

ABSTRAK

Kata Kunci:
COVID-19,
forecast,
time series

COVID-19 (Coronavirus Disease 2019) masih menjadi masalah bagi seluruh dunia. Penyakit ini mulai melanda akibat adanya kontak langsung dengan seafood market di Wuhan, Provinsi Hubei, China. Kasus COVID-19 secara global maupun di Indonesia sendiri masih terus mengalami peningkatan. Oleh karena itu, penting untuk dilakukan peramalan kasus yang akan datang sebagai bentuk kewaspadaan dan bahan merumuskan strategi dalam mengendalikan penyebaran maupun pengadaan sistem kesehatan. Penelitian ini bertujuan untuk memprediksi kasus harian COVID-19 di Indonesia. Penelitian ini termasuk studi non-reactive dengan mengumpulkan data kasus harian COVID-19 pada 1 Oktober – 31 Desember 2020 yang berasal dari website Gugus Tugas Percepatan Penanganan COVID-19 Indonesia. Hasil penelitian menunjukkan bahwa model yang fit untuk menggambarkan kasus COVID-19 di Indonesia adalah ARIMA (5,1,0) dengan nilai signifikansi model sebesar 0,000 dan constant sebesar 0,049 (p value <0,05), Ljung-Box Q sebesar 0,880 (p value >0,05) dan normalitas residual sebesar 0,330 (p value >0,05). Hasil forecasting *selama tiga bulan (Januari – Maret 2021) menunjukkan angka yang cenderung mengalami peningkatan. Peningkatan kasus bisa terjadi akibat beberapa faktor seperti lingkungan, perilaku, pelayanan kesehatan dan genetik. Karena itu diperlukan peningkatan kerjasama antara pemerintah dan masyarakat sehingga upaya menekan pertumbuhan kasus COVID-19 lebih optimal.*

INTRODUCTION

Coronavirus Disease 2019 (COVID-19) is still a global issue for the entire world. The disease began to spread in December 2019 due to direct contact between people with the seafood market in Wuhan, China. This virus is categorized as Severe Acute Respiratory Syndrome (SARS), specifically SARS-CoV-2, which can infect the respiratory tract (1). Initially, the virus only infects animals, and it is still unclear if humans can catch it as well. However, with the increase in confirmed Wuhan cases, it was finally stated that it is contagious amongst humans.

Transmission of COVID-19 may occur through contact and droplets, indirect or direct contact, also near contact via saliva and

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respiratory secretions, as well as airway droplets that come out when an infected person sneezes, coughs, speaks or sings (1). Indirect contact transmission where contact occurs between vulnerable hosts and contaminated objects or surfaces (fomite transmission) may also occur. The transmission can occur from floating nuclei droplets (aerosols) in the air and travel long distances. Other transmissions are biological samples, including urine and feces from some patients found in this virus's RNA. It can also be found in blood plasma/serum because it can replicate in blood cells but at low concentrations.

COVID-19 infections generally cause mild to severe respiratory illnesses and death, while some people infected with the virus have never shown any symptoms. The proportion of entirely asymptomatic cases varies from 6% to 41%. (1). The proportion of asymptomatic patients varies due to increased comorbidity in older age groups. Common symptoms of COVID-19 are cough, fast/difficulty breathing, fever/chills, muscle/body pain, nausea, diarrhea, and loss of taste/smell. There are emergency signs that can get medical attention immediately, in addition to usual symptoms, including trouble breathing, constant chest pain, exhaustion, unable to get up, or looking bluish on the lips/face. Symptoms can appear gradually (from mild to severe) and emerge after 2-14 days of virus exposure.

Ever since announced as a pandemic, COVID-19 has seriously affected many countries around the world. Data shows the total worldwide cases of COVID-19 on December 31st, 2020 was 83,884,211 cases with 1,826,376 death cases and 60,281,978 recovered patients. The ten countries with the highest cases of COVID-19 in a row are the United States of America, India, Brazil, Russia, United Kingdom, France, Turkey, Italy, Spain, and Germany (2).

Indonesia's COVID-19 cases have also been increasing. The total number of COVID-19 cases in Indonesia per December 31st, 2020 was 743,198 cases, with 22,138 death cases and 611,097 recovered patients. Ten provinces with the highest cases were DKI. Jakarta, West Java, East Java, Central Java, South Sulawesi, East Kalimantan, Riau, West Sumatra, Banten, and Bali (3). The spread of this disease can be controlled by preparing anticipation based on COVID-19 case predictions using methods for statistical modeling. These models can make short-term and long-term estimation of the disease's spread to provide an overview of the number of healthcare services needed to reduce the impact from another sector significantly.

A chronological sequence of observations is a time series (4). Data movement patterns or variable values of time series data are known. Time series data as the basis for current decision-making, forecasting future trading or economic conditions, and planning future activities. Stationary data is an essential form of time series. A time series is purely stationary if a change in the time source does not alter its characteristics. Data transformations stabilize the data's variance in statistical work since non-constant variance is very common in time-series data. Meanwhile, to stabilize when data is non-constant in mean, use data differencing.

ARIMA (Autoregressive Integrated Moving Average) is one of the most common models in time series. ARIMA model consists of three primary stages: identification, evaluation and testing, and diagnostic control. The ARIMA model can be used to carry out forecasting if the model obtained is satisfactory. However, ARIMA is a model that ignores independent variables when forecasting (4). The research aims to forecast daily cases of COVID-19 in Indonesia. This research can be an overview of future cases. Both the government and the public will be more vigilant in dealing with the growing cases of COVID-19 in Indonesia.

METHODS

This research is included in the design of non-reactive studies because it does not give any treatment to research subjects. The research starts from October - to December 2020, and such as data collection, cleaning, input, testing, and interpreting. The COVID-19 daily positive case data on October 1st to December 31st, 2020, originated from the COVID-19 Task Force in Indonesia (www.covid19.go.id) and is already open to the public. Data collection is accessing the website, consisting of cumulative COVID-19 case confirmation data for three months (92 days).

The time-series application consists of at least 60 points to provide a good model. Data cleaning is ensuring there is no double or empty data. Then, input and data testing using SPSS 2.1 software. Data analysis stages consist of stationary data, time series model determination, residual normality test, overfitting test, and forecasting for three months (January 1st to March 31st, 2021).

Forecast for three months because there is an indication of increased crowds due to religious new year celebrations. The stationary data test aims to find out the average value and constant data variants. The time series model determination aims to find the best model before forecasting and overfitting tests to ensure that the model used is suitable for forecasting. This study used an alpha standard of 5% (0.05). The model is called fit when it meets assumptions such as constant value and model (p value <0.05), Ljung Box-Q (p value>0.05) normal distributed residual value (p value>0.05). Ljung Box-Q value serves to know the value of autocorrelation simultaneously.

RESULTS

The first case of COVID-19 in Indonesia occurred in March 2020, and it continues to increase. The government also issued social distancing and lockdown policies. This strategy aims to disrupt Indonesia's COVID-19 transmission chain. Nevertheless, this situation also contradicts the government's directive, which states that more patients still get COVID-19 confirmed. Figure 1 shows that the COVID-19 daily cases are still rising in Indonesia by December 31st, 2020.

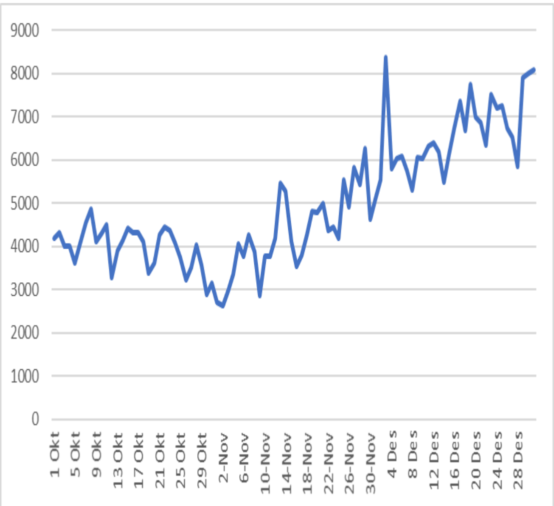

Figure 1. Graph of Daily Cases of COVID-19 in Indonesia from October 1st – December 31st, 2020.

Stationary Data

The results showed that the data was not stationary in means; therefore, differencing was done once and then ACF and PACF charts were obtained as it can be seen on Figures 2 and 3. A stationary time series ACF plot is to acquire a fundamental understanding of AR or MA terms to match the data to create a better model. If the ACF plot at the first lag has negative auto-correlation, it was suggested using terminology from MA. If a sharp cutoff positive in the PACF plot of the different time series, to the model, add AR terms. Figure 2 shows an exponential presence, while Figure 3 indicates the presence of bars clipped at lags to 1, 3, and 5.

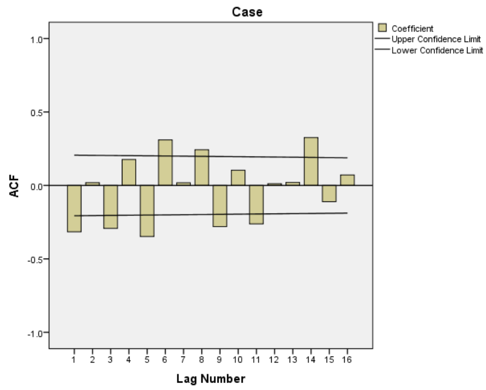

Figure 2. Graph of Autocorrelation Function (ACF).

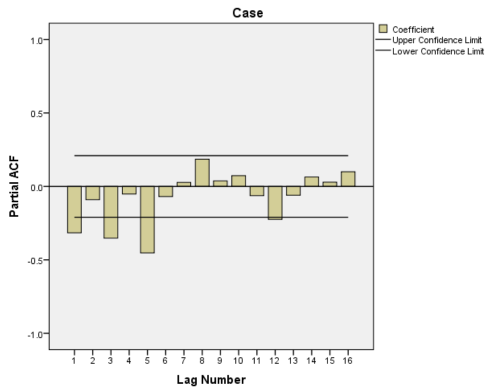

Figure 3. Graph of Partial Autocorrelation Function (PACF).

Time Series Model

Based on the test, the possible time series model is ARIMA [1,1,0], ARIMA [3,1,0], and ARIMA [5,1,0]. Table 1 shows that the suitable model with fulfilled assumptions is ARIMA [5,1,0] because the constant and the model value is less than 0.05, and the Ljung-Box Q value is more than 0.05.

The residual normality test used Kolmogorov Smirnov in one sample. The test result obtained a value of 0.330 (p value >0.05), which means residuals normally distributed and accepted assumptions.

Over Fitting

Even though the ARIMA [5,1,0] model has already fulfilled the assumptions, it still needs to over-fitting the test with another model to ensure that the selected model is entirely fit. Furthermore, the testing with the Moving Average/MA [1] model obtained a p value in the constant model and Ljung-Box Q of 0.880, 0.000, and 0.000. The MA [1] model does not fit because the constant and Ljung-Box Q values are insignificant.

Table 1. Statistics Model

Possible Model		**Sig.**	**Ljung-Box Q**
ARIMA [1,1,0]	Constant	0.444	0.000
	Lag 1	0.003	
ARIMA [3,1,0]	Constant	0.264	0.000
	Lag 1	0.000	
	Lag 2	0.039	
	Lag 3	0.001	
ARIMA [5,1,0]	Constant	0.049	0.848
	Lag 1	0.000	
	Lag 2	0.000	
	Lag 3	0.000	
	Lag 4	0.017	
	Lag 5	0.000	

Forecast

The next stage is forecasting for three months. Figure 4 shows that daily cases of COVID-19 tend to increase.

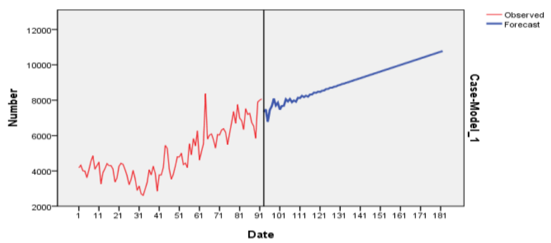

Figure 4. Graph of COVID-19 Daily Cases Forecast from January to March 2021

DISCUSSION

The results showed that the suitable model for forecasting COVID-19 positive cases in Indonesia for January to March 2021 is ARIMA [5,1,0]. A study aims to forecast positive cases, recovered patients, and death cases of COVID-19 in Indonesia from March 2nd to April 17th, 2020, was using ARIMA [0,1,1]. The forecast results showed an imbalance between the increase in positive cases and recovering patients with the decrease in death (5). This study suggests that people still do not comply with the government rules (social distancing, wearing masks), thus, insufficient medical personnel, and the shortage of standard COVID-19 handling equipment is one reason for the inadequate handling of the positive patient.

One study also used the ARIMA model to predict the mortality rate of COVID-19 in Jakarta, Indonesia, from January to March 2020 (6). Factors that may trigger the mortality rate of COVID-19 are difficult to identify (because most cases found are asymptomatic), and a limited number of both health workers and infrastructures (significantly if health workers infected with COVID-19 will impact the services). In addition, easy access to health services is also important. It is essential to advise the public to recognize unusual symptoms such as breathlessness or chronic cough to seek medical treatment to diagnose the virus early.

However, different studies show different results. A study aimed to predict confirmed COVID-19 cases using ARIMA [0,1,0] with a Bayes Information Criteria (BIC) of 4,170 and a Mean Absolute Percentage Error (MAPE) value of 16.01 in Malaysia. Forecast testing conducted for 14 days (April 18th to May 1st, 2020) shows a declining number (7). A research in the same place, Malaysia and Sarawak, also reported forecasting using ARIMA [1,1,1]. Test results show that forecasts for 14 days tend to decline. This decline may occur because Malaysia has reached the peak of cases. However, there is a spike in cases in Sarawak that does not close the possibility of a new wave (8)

Other research forecasting the ARIMA model in confirmed COVID-19 cases every day in some countries show different models and trends every day. The forecast is for 17 days, from March 5th to 17th, 2020. Model test results showed ARIMA models [2,1,0] for China, ARIMA [1,0,0] for South Korea, ARIMA [3,1,0] for Thailand, ARIMA [2,2,2] for Italy, and ARIMA [2,3,0] for Iran. In China and Thailand, there are relatively stable conditions. China and Thailand are quite successful in implementing various case-control policies. South Korea's trend tends to decline, while Iran and Italy's trend is still volatile (9).

Research in other countries such as the United States, Brazil, Russia, India, and Spain with the same purpose. Forecast for 77 days (June 30 – September 15, 2020) using the ARIMA model. ARIMA models that are suitable for the United States are ARIMA [1,2,1], ARIMA [3,1,2] for Brazil, ARIMA [3,0,0] for Russia, ARIMA [4,2,4] for India, and ARIMA [4,2,4] for Spain. Forecast results show that Russia and Spain will soon experience a decline in cases, while the United States, India, and Brazil continue to increase. India has seen an increase in cases as migrants move out of Delhi and Mumbai as the government has lifted its lockdown policy. This condition ranked India third with the highest COVID-19 cases as of the end of June 2020 (10).

Increased or decreased cases may occur due to the influence of several factors, including the environment, behavior, health care, and genetics. A study stated that air temperature and air quality index ($PM_{2.5}$ and NO_2) link to increased reported cases. The higher amount of $PM_{2.5}$ and NO_2 in the ambient air can increase the transmission of COVID-19, which automatically enhances new cases. Air temperature has a negative correlation, which means that when the air temperature is lower, it can get a higher chance of COVID-19 spreads (11). The results align with other studies that NO_2 has a significant positive relationship with the severity and death cases (12). Therefore, wearing a mask is obligatory to prevent virus contamination and reduce air pollution's adverse risk when going out.

Regions with railways, toll roads, national highways, or airports are at greater risk of rising cases of COVID-19. These results suggest that, as occurred during the COVID-19 outbreak, easy public mobility and transportation should have made rapid transmission easier (13). Especially in a town that becomes the center of politics, culture, economy, and transport that allows villagers to work or even settle for travel by train, car, or bus. Many of them decided to return home during the epidemic, thus spreading COVID-19 to the surrounding area. For example, DKI Jakarta is Indonesia's capital and has a very dense government hub; therefore, policies related to COVID-19 regulation in DKI Jakarta are different from other regions.

The probability of COVID-19 transmission rises in low air temperatures, moderate humidity, and intense wind speeds (13). Other studies have also shown that temperature is one of the factors correlated with the increasing spread of COVID-19 cases (14). One study also recorded that weather indicators are critical and inseparable in forecasting and preventing the transmission of COVID-19 (15). Colder areas should take even stricter steps to prevent the coronavirus from being worse. It is also the case that if the novel coronavirus co-exists with humans for a long time, both countries (Mexico and China) will bring together anti-epidemic police.

Behavioral factors tend not to comply with health protocols to prevent COVID-19 disease. Compliance in implementing this protocol may be affected by various factors. The level of education is significantly related to COVID-19 prevention behaviors such as staying at home, avoiding public meetings (weddings, parties), and taking immunity boosters (honey, ginger, dates). Educated people actively obtain information about COVID-19 from various information media (16). In line with that research, higher education institutions require everyone to always wear masks when leaving home and constantly washing hands with soap. People with lower education levels will have less attention to their behavior because they tend to have less access to COVID-19 information (17).

Adherence to health protocols relates to individual perceptions about the risk of infection or behaviors that may increase it. Including reducing the number of people encountered each day, avoiding using public transportation, surface cleaning of regularly touched items, washing hands with soap and running water, using masks when out of the house, and avoiding going to hospitals/clinics (18). This understanding may be formed by the accessible information from the government's official public health system.

In addition to the level of education and perception, behavior during pandemics is influenced by psychological conditions. If the psychological pressure is too high, then the person will tend to perform extreme protection measures. The relationship between psychological distress and behaviors that were anticipated by WHO is correlated. The aforementioned behaviors such as taking unnecessary vitamins or drugs for self-protection, using hand dryers after washing hands, and exposing the body with ultraviolet lamps (19). They are doing all of these behaviors, assuming they can kill the COVID-19 virus. This excessive behavior is feared to increase the health system's cost due to medications' side effects that the body does not need.

In this case, health care factors affect health workers in providing services during the pandemic. More than 50% of health workers (radiology) are in a high anxiety level of 7-10 during the pandemic. This condition is due to the excessive workload, personal health, and the health facility's willingness to treat patients during the pandemic (20). High anxiety levels in health workers are caused by social factors such as living with older people, chronic diseases, low immunity, respiratory diseases and organizational factors such as working in health facilities that receive and directly handle COVID-19 patients (21).

During this pandemic, wearing complete Personal Protective Equipment (PPE) also influences health workers' mental condition. Complaints of health workers when wearing PPE are significantly related to anxiety. The perceived complaints are excessive fatigue, not freely going to the bathroom, thirst, headache, heat, and pressure in some parts of the body (22). In line with that, research also showed indications of heat-related illness symptoms in health workers who use PPE. Complaints are feeling hot, feeling uncomfortable, dizziness, fatigue, dehydration, headache, profuse sweating, and exhaustion (23). This condition can affect cognitive tasks such as making decisions, solving complex problems, recovery of short-term memory, and attention concentration.

Genetic factors can also increase the risk of being infected with COVID-19. Older people (85 years old and over) have a COVID-19 infection risk of 1.4 times than young people (18-24 years old). Also, people with comorbidity are 1.7 times riskier of COVID-19 than people without comorbidity (24). The comorbidity includes diabetes, hypertension, stroke history, chronic or terminal kidney disease, HIV (Human Immunodeficiency Virus), asthma, or smokers. Another study also shows that comorbidity can be more significant than the risk of being infected by COVID-19. The risk for people with diabetes is 1.74 times higher than for people without diabetes, and the risk for people with hypertension is 1.39 times higher than for people without hypertension (25).

CONCLUSIONS AND SUGGESTIONS

Conclusion

Time series test results showed that the best model for forecast Indonesia’s daily cases of COVID-19 is ARIMA [5,1,0] with a model significance of 0.000 and constant of 0.049 (p value <0.05), Ljung-Box Q is 0.880 (p value >0.05) and residual normality is 0.330 (p value >0.05). Daily COVID-19 case forecasting for three months from January 1st to March 31st, 2021 showed that it tends to increase. The increase in cases can be caused by a variety of factors, including the environment (physical), behavior (adherence to health protocols), health services (mental health workers' mental state), and genetics (increasing the risk of infection).

Suggestion

In this case, initiating higher cooperation between the government and the community increases supervision related to all government policies to reduce cases. For example, by conducting inspections at cafes or eatery places every 9 pm, closing the village's entrances or alleys at 11 pm, increasing the frequency of mask operations on the street once a week, sanctioning people who do not wear masks when leaving the house. Also, it is necessary to have strict regulations related to people who often travel between cities using public transportation, such as requiring self-quarantine and antigen tests before and after traveling to reduce the possibility of spreading the virus to family members.

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