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The accuracy of forecasting results of the Box-Jenkins method for time series analysis on the number of pneumonia patients

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ABSTRACT

Accurate forecasting in pneumonia cases is crucial for healthcare providers to effectively allocate resources and plan for patient care. This quantitative study employs a non-reactive approach, employing time series analysis through the autoregressive integrated moving average (ARIMA) Box-Jenkins method on secondary data. Monthly data simulations spanning 1, 3, and 6 months were conducted, divided into two groups: initialization data from 2016-2019 and actual data from 2020. The goal was to assess the forecasting accuracy using the Box-Jenkins method for pneumonia cases at Kamonji Public Health Center, Palu. The 1-monthly data simulation, with 48-time series as initialization data, yielded an appropriate forecasting model, ARIMA (1,1,1), predicting 289,166 pneumonia patients. However, the 3-monthly and 6-monthly simulations did not yield suitable forecasting models. In conclusion, none of the data simulations accurately predicted the number of pneumonia cases, often overestimating compared to actual data. Recommendations include using data spanning more than five years to enhance accuracy. For stakeholders, forecasting analysis in pneumonia cases aids in predicting cases, identifying risk factors, understanding prognosis, and tailoring treatment plans. Data-driven models empower healthcare providers to make informed decisions and optimize patient care. Accurate pneumonia forecasting remains essential in efficient healthcare resource allocation and planning.

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1. INTRODUCTION

Pneumonia is an acute infection or inflammation in the lung tissue caused by various microorganisms, such as bacteria, viruses, parasites, and others. Pneumonia can affect anyone, for instance children, adolescents, young adults, and the elderly. However, it is more vulnerable at the age of toddlers and the elderly. The incidence of pneumonia is more common in developing countries [1]–[3]. The infection makes it difficult for a child to supply oxygen into the respiratory tract due to pus and fluid, causing tightness in the child [4]–[6].

Pneumonia is one of the largest single infectious causes of death in children under five. The World Health Organization (WHO) estimates that the mortality of children under five due to pneumonia worldwide is 15%, and more than two million children are killed by pneumonia [6], [7].

According to UNICEF, in 2018, the mortality rate of pneumonia was more than 800,000 children under five in the world or 39 children per second die. The highest order of under-five deaths due to pneumonia in other countries includes Nigeria, as many as 162,000, India, 127,000, and Pakistan 58,000. Meanwhile, Indonesia is ranked sixth, with 19,000 children estimated to have died from pneumonia. Global estimates show that in one hour, there are 71 children in Indonesia catch pneumonia [8], [9].

Based on the reporting data of the acute respiratory infections (ISPA) Sub-Directorate in 2018, the incidence (per 1,000 toddlers) in Indonesia was 20.06%, almost the same as the previous year, which was 20.56%. One of the efforts to control pneumonia is to increase the discovery of pneumonia in children under five. The national estimate of pneumonia cases is 3.55% but estimates of pneumonia cases in each province use different numbers according to what has been determined [7], [9], [10]. The coverage of pneumonia among children under five in Indonesia was 20-30% from 2010 to 2014. Starting from 2015 to 2020, there was an increase in coverage due to changes in case estimates. The coverage of pneumonia discovery in 2016 was 65.3%, decreased in 2017 to 51.2%, and in 2018 increased to 56.5%. In 2019 it amounted to 52.9%, but in 2020 it decreased to 34.8% [1], [9], [10].

According to data from the Central Sulawesi Provincial Health Office in 2019, the coverage of the discovery of under-five pneumonia was very low in 2012. Still, year by year, it continued to increase and peaked in 2015 but starting from 2016, it decreased. In 2016, it was 67.9% and continued to decline until 2020 at 37.2%. Based on reports from the Public Health Office in Palu, Pneumonia incidence rate has fluctuated every year in the last three years. In 2018 there were 1,781 pneumonia cases. In 2019, there was a significant decrease to 643 cases, and in 2020 there was an increase to 703 cases. From the data from the Public Health Office in Palu, the health center with the most pneumonia cases was Kamonji Health Center, with a prevalence of pneumonia in 2018 at 317 cases, and 2019 experienced a significant decrease of 145 cases and decreased in 2020 to 92 pneumonia cases [10]–[14].

Factors that cause pneumonia in children include low birth weight, insufficient exclusive breastfeeding, malnutrition, vitamin A deficiency, and exposure to air (cigarette smoke). Males are more likely to be affected by pneumonia because the diameter of the respiratory tract in males is smaller than in females, or there is a difference in endurance between boys and girls [11], [15], [16]. Low birth weight children are more susceptible to infection due to incomplete formation of immune substances [11], [17]–[19].

The impact of pneumonia on children is death and disability, but the prevention of pneumonia has not yet received attention [14], [20], [21]. A child's future development is greatly influenced by what happens to them during their toddler years. If the child is more susceptible to disease, it can cause death. Most are caused by pneumonia, diarrhea, malaria, measles, and malnutrition [22]–[24]. One of the efforts to reduce morbidity and mortality rates due to pneumonia in children under five is determined by the success of early discovery and management of pneumonia among children under five at health centers [11], [22], [24].

The forecasting method is an activity that aims to estimate an event in the future and is a tool to plan effectively and efficiently [25], [26]. Forecasting activities can be used on problems that exist in society, including one of them, namely health problems. The time series forecasting method is used to determine the development of an event and can be used to make forecasts based on trend lines or regression [27]–[29]. Based on time series forecasting is a future value that is a mathematical function of past values, and the function model is based on the time series itself without being influenced by external variables [27].

The Box-Jenkins method or commonly referred to as the autoregressive integrated moving average (ARIMA) method, is one of the time series quantitative forecasting methods that aims to forecast the value of a variable in the future based on the past value of the variable without thinking about why there is an increase in certain values of the variable taken [27], [30], [31]. If the variable Yi is assumed to be a series of observations, ti is a time variable that moves from the past to the future in the same direction. Hence, series of data consisting of Yi above and a time function from ti is called a time series [32]–[34]. When combined into Yi, a series of data or variables that depend on a time, then Yi can be called a periodic series.

The Box-Jenkins method is a popular model used for time series forecasting. It is an autoregressive integrated moving average (ARIMA) model that focuses on the dependent variable and ignores the independent variable. The ARIMA model is known for its accuracy in short-term forecasting, but its accuracy decreases for long-term forecasting. This is because the ARIMA model tends to produce flat forecasts for longer periods [27], [32], [35]. The ARIMA Box-Jenkins method has been used by Widiastuti [36] to show the results of forecasting accuracy on the number of Diabetes Mellitus patients at Dr Soetomo Surabaya General Hospital based on data from 2001 to 2005. In his research, he used initialization data and actual data for 1-monthly, 2-month, 3-monthly, and 4-month data as his time series to do this forecasting. Therefore, the researcher investigated the ARIMA Box-Jenkins forecasting method using initialization data

and actual data of one month, three months, and six months as a periodic series to determine the accuracy of the number of pneumonia patients.

There are several purposes for people doing time series analysis. First, to study the patterns of information presented by time sequence by making mathematical demonstrations; second, to perform forecasting to anticipate future events [37]. In terms of health and medicine, forecasting is generally used to predict the number of disease cases in the next few years and as a tool to develop a policy and make good decisions.

Based on the result of study entitled the application of the Box-Jenkins ARIMA method to forecast dengue fever cases in East Java Province, the forecasting results are adequate and feasible to use. In another study entitled the application of the Box-Jenkins method to predict the number of cases of acute respiratory infections at the Arifin Achmad Hospital, Riau Province, Indonesia. The forecasting results are predicted to be stable compared to the previous year, so the researcher sees the conclusion from the case example above that actual or current data compare the importance of forecasting accuracy.

Based on the background, this study was conducted because previous researchers only conducted initialization data for four months and rarely conducted research to determine the accuracy of forecasting results with the Box-Jenkins method. The researcher is interested in investigating the accuracy of forecasting results of Box-Jenkins method time series analysis on the number of pneumonia patients at Kamonji Public Health Center.

2. RESEARCH METHOD

This research is quantitative research with a non-reactive or unobstructive approach. Non-reactive research is research that does not require a response from the subject under study, and there is no interaction between the researcher and the research subject. The data used in the study were secondary. Pneumonia disease data from 2016 to 2020 were recorded at the public health center. The ethical permission was obtained by researchers from the Institutional Review Board at Universitas Tadulako. No. 0121052. This study was conducted at the Kamonji public health center in October 2021. The population in this study was seen in the number of people with pneumonia disease from 2016-2020 at Kamonji public health center. The samples in this study were reports of pneumonia patients at the Kamonji public health center from 2016-2020. The data analysis used the Time Series Analysis Box- Jenkins Method. The Time Series Analysis Box- Jenkins Method has applied for different time frames in order to decide accuracy based on dataset. Estimation parameters based on possible ARIMA model were checked and evaluated as data analysis procedure to find the best forecasting model. However, only forecasting with the Box-Jenkins method on a 1-monthly time series totaling 48 data obtained a suitable model.

3. RESULTS AND DISCUSSION

3.1. Simulation of the 1-monthly time series data from 2016 to 2020

Table 1 is 1-monthly time series data from January 2016 to December 2020 from the medical records of Kamonji health center, divided into two data groups. The first group of initialization data was from January 2016 to December 2019 as many as 48 data were used to obtain the best forecasting model. In the second data group, as actual data was from January-December 2020, as many as 12 data were used as validation data.

Table 1. The 1-monthly time series data from 2016 to 2020

Month	Initialization data				Actual data
	Year 2016	Year 2017	Year 2018	Year 2019	Year 2020
January	18	33	32	11	4
February	11	26	30	53	4
March	10	33	37	51	14
April	23	27	43	19	5
May	21	38	24	11	3
June	20	24	21	7	4
July	18	23	34	6	23
August	70	51	21	9	20
September	88	25	19	25	16
October	72	18	7	7	8
November	107	13	22	42	5
December	78	25	27	15	4

3.1.1. Model Identification for the 1-monthly data plot

The first stage of model identification for 1-monthly data plot involves viewing data plots using Minitab software and obtaining the 1-monthly Pneumonia data time series plot. This process allows researchers to visualize the data and identify any patterns or trends that may be present. By using Minitab software, researchers can easily generate plots and graphs to analyze the data. This stage shown in Figure 1:

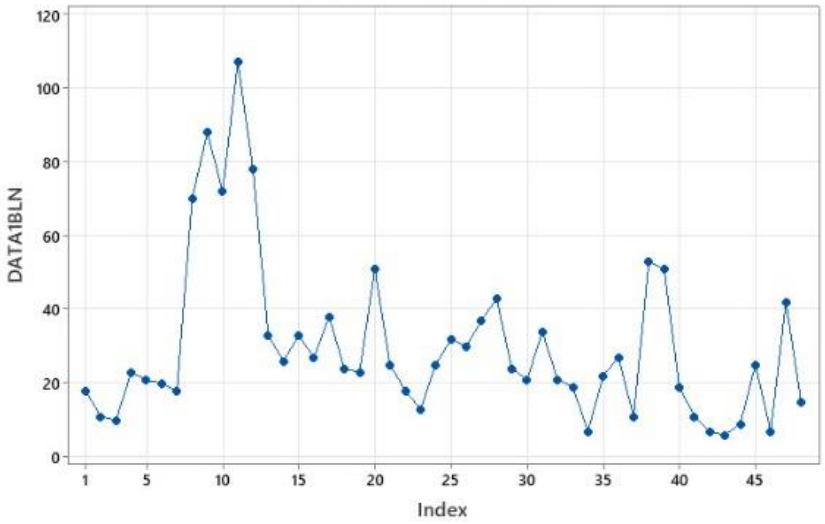

Figure 1. Time series plot of 1-monthly pneumonia data

The time series plot indicates that the plot is not stationary because there are still fluctuations in the data that tend to go up and down, or the data is not constant over time. Data not stationary in variance can be known from the Box-Cox transformation table in the Minitab software, which has a rounded value in the lambda box (λ), not 1 but 0, which is shown in appendix I. Data transformation is carried out in Minitab software to make the stationary data in variance until the data has obtained a rounded value of 1 in the Box-Cox Transformation table shown in appendix II thus the data is said to be stationary in variance. Figure 2 shows that the data is stationary in variance and mean. The data plot pattern is constant. The data differencing process is carried out once to make the data stationary in the mean, and the time series plot is obtained as follows:

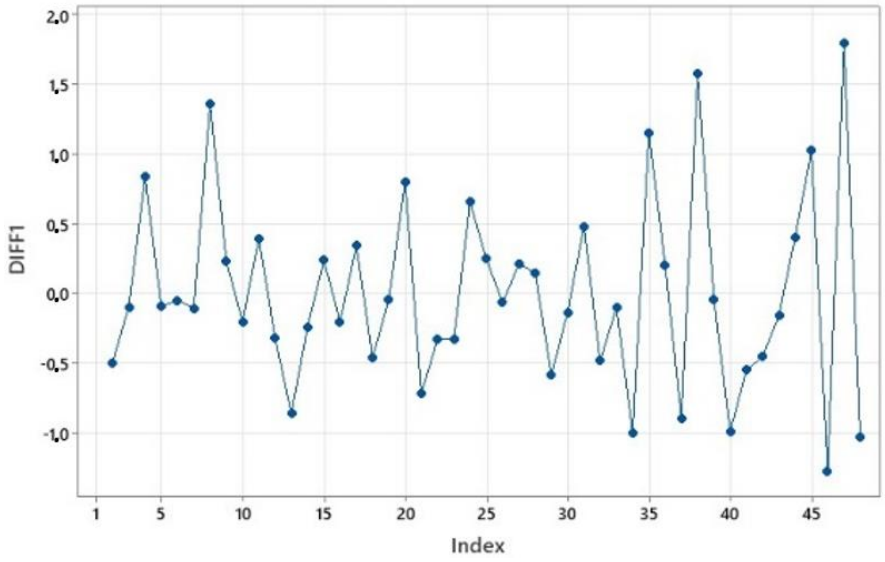

Figure 2. Time series plot of 1-monthly pneumonia data (stationary)

The second stage is by estimating the ARIMA model Through ACF Plot and PACF Plot using Minitab software. The ACF (Autocorrelation Function) plot is used to identify the MA (Moving Average) component of the ARIMA model, while the PACF (Partial Autocorrelation Function) plot is used to identify the AR (Autoregressive) component. The Figure 3 shows 1 lag out of bounds or cut off, shown in the first lag out of bounds, showing the basic form of the MA (1) model. The estimated possible base ARIMA model is (0,0,1). The Figure 4 shows that the PACF value that goes out of bounds or cut off is 1 lag, shown in the first lag out of bounds, so it shows the basic form of the AR (1) model. The basic ARIMA model estimate that is possible is (1,0,0). With the differencing process, the order d=1 refers to the previous identification to make the data stationary. Then the temporary ARIMA model that is thought to fulfill is ARIMA (1,1,1) (1,1,0) (0,1,1) and (0,1,0).

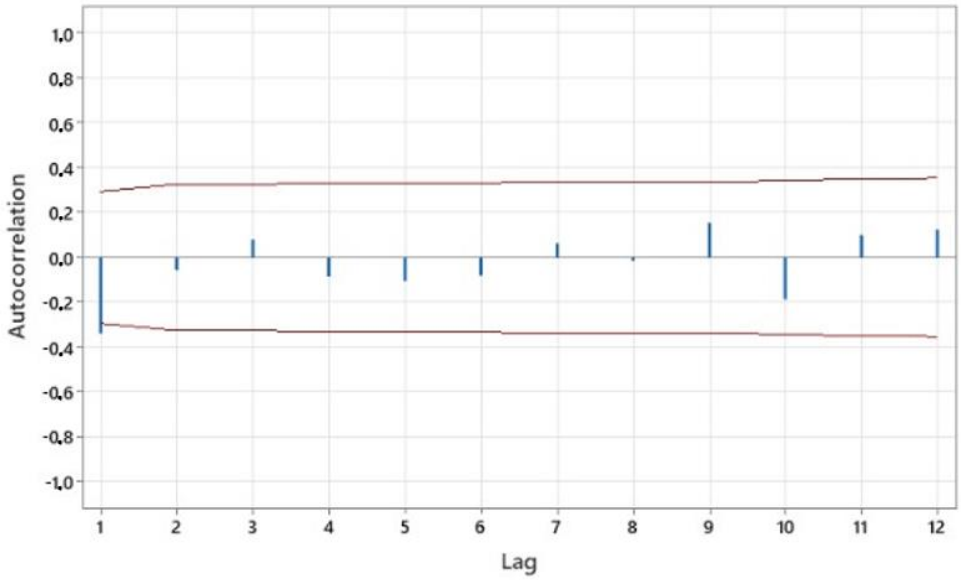

Figure 3. ACF plot of 1-monthly pneumonia data

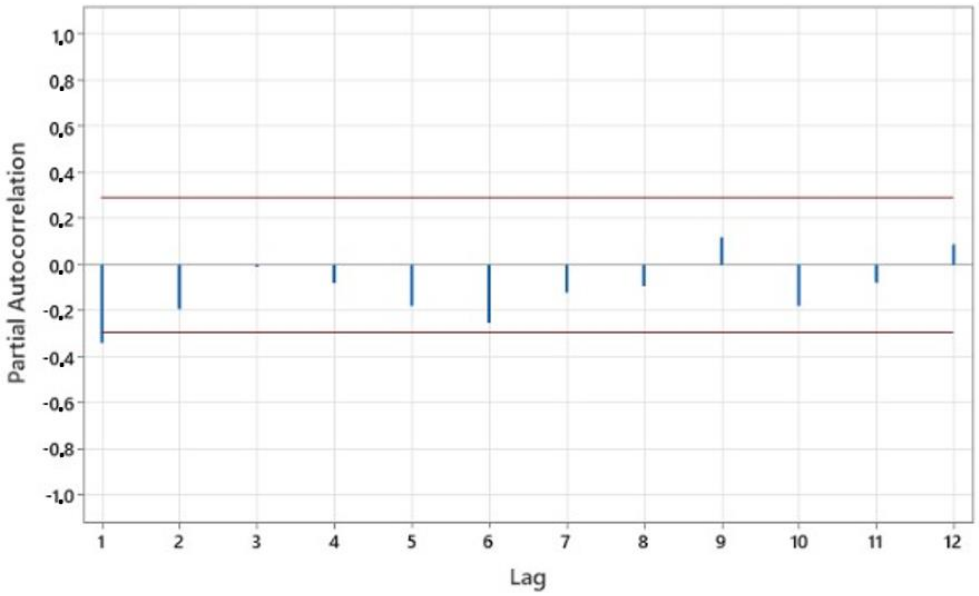

Figure 4. PACF plot of 1-monthly pneumonia data

3.1.2. Parameter estimation for the 1-monthly data plot

In parameter estimation, the autoregressive (AR) and moving average (MA) were checked and evaluated based on data plot. The result of parameter estimation of ARIMA (1,1,1) confirms that significant result with obtained the p-value of AR 1 is 0.014. Additional, the parameter estimates of the ARIMA model (0,1,1) model also show the p-value of MA 1 is 0.001.

3.1.3. Diagnostic checking test using white noise assumption test

The white noise model represents the nature of noise in 1-monthly data plot for pneumonia patients. The results of the ARIMA (1,1,1), (1,1,0), (0,1,1) have p-values above 0.05. Therefore. It can be included the errors that occur have followed the white noise process. After estimating the parameters of each model, the best model can be selected from all possible models by looking at standard measures of forecasting accuracy.

Based on Table 2, the selected model is the model that has the lowest prediction error rate, which is reflected in the small MS value. Thus, the best model is the ARIMA (1,1,1) model, which has the smallest MS value of 0.368368 compared to other ARIMA models. In Table 2, the forecasting results for the ARIMA (1,1,1) model are obtained.

Table 2. The ARIMA model table with MS value

Model	MS
ARIMA (1,1,1)	0.368368
ARIMA (1,1,0)	0.407214
ARIMA (0,1,1)	0.391081

3.1.4. Accuracy of forecasting amount

Table 3 compares forecasting results for each month. This time series can be done for monthly forecasting because the forecast results are obtained monthly. Meanwhile, forecasting for 1 year can also be done; the results obtained are the number of forecasts =289,166. In contrast, the actual amount =110, thus the accuracy of the forecasting amount does not occur in this 1-monthly data simulation because the difference between the results of the amount of forecasting and the actual amount of data is very large, namely 179,166 or has a very low accuracy value.

Table 3. The 1-monthly time series forecasting results

Months	Forecasting	Actual
January	19.0056	4
February	21.4857	4
March	23.0212	14
April	23.9719	5
May	24.5606	3
June	24.9250	4
July	25.1507	23
August	25.2904	20
September	25.3769	16
October	25.4304	8
November	25.4636	5
December	25.4841	4
Total	289.166	110

Generally, forecasting with the Box-Jenkins method on a 1-monthly time series totaling 48 data obtained a suitable model for initialization data, namely ARIMA (1,1,1) (1,1,0) (0,1,1) and (0,1,0). Before the ARIMA model is known, the data is not stationary in both variance and mean. Obtaining data that is stationary in variance is done in Minitab software which can be seen in the Box-Cox Transformation table. After being stationary in variance, the differencing process is carried out 1 time to obtain stationary data in the mean. Based on the general ARIMA (p, d, q) model, the value of order p is the value of the AR component coefficient. The value of p is 1, which is obtained from the time lag value that comes out of the limit or cut off at time lag 1 through the calculation of PACF or partial autocorrelation function. The value of d is the differencing process which is done once. The q value is the value of the MA component coefficient. The value of p is 1 obtained from the time lag that comes out of the limit or cut off at time lag 1 through the calculation of ACF or Autocorrelation function. After obtaining a suitable and feasible model, namely ARIMA (1,1,1), the number of forecasting results was obtained 289,166, which means that the number of forecasting results is not correct

when compared to the actual data in 2020, which amounted to 110 because it produces a high number of forecasts compared to the number of pneumonia patients in 2020. One of the factors causing the decline in the number of people with pneumonia in 2020 was the COVID-19 phenomenon, so the lack of people visiting the Kamonji public health center. The 1-monthlyly simulation data is the most feasible to use for forecasting because the data has a real value and not the amount of data compared to the 3-monthly and 6-monthly data simulations. This study focuses on forecasting dengue hemorrhagic fever cases using the ARIMA model in the Asahan district. The ARIMA model is a widely used time series forecasting method that can be applied to various fields, including epidemiology [38]. Related studies in asian and western context also shows that 1-montly data simulation is suitable for forecasting methods [33], [34], [39]–[42].

For 3-monthly time series data with 16 group as initialization data, No ARIMA model is suitable and feasible for forecasting even though the 3-monthly data has followed the ARIMA requirements, namely stationary in variance and mean. However, it does not show the limited results to determine the basic AR and MA models seen in the ACF and PACF tables. Therefore, it cannot determine the appropriate model.

In addition, The Box-Jenkins forecasting method uses 6-monthly time series data with a total of 2 data as the initialization data. However, it does not get the appropriate ARIMA model because the time series used does not follow the ARIMA requirements, namely stationary in variance and mean. However, the 6-monthly data is stationary in variance. Still, when the differencing process is carried out to determine whether the 6-monthly data is stationary in the mean, it turns out that the 6-monthly data is not stationary because it has a data plot that is not constant. So, the time series data for this 6-monthly data is not feasible to find the ARIMA model, and in the end, the 6-monthly time series data cannot be forecast.

4. CONCLUSION

Overall, the forecasting results of the Box-Jenkins method time series analysis on the number of pneumonia patients at Kamonji public health center confirm that only forecasting with the Box-Jenkins method on a 1-monthly time series totaling 48 data obtained a suitable model. The 1-monthly Pneumonia data time series plot as presented in Figure 1 allows researchers to visualize the data and identify any patterns or trends in predicting case numbers, identifying risk factors, understanding prognosis, and developing personalized treatment plans of pneumonia patients. For future research, we also recommend other health care or researchers are expected to master the steps performed in the Box-Jenkins method of time series analysis and must be able to pay attention to the graph in the time series data plot. It also can be used as consideration for further research using a longer time series. The results of this study are expected to provide example how to utilize the Box-Jenkins method time series analysis and to give the input to the Kamonji public health center in Palu City if the data in the future experiences an increase in pneumonia patients so that they can take an anticipatory attitude and make decisions.

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