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Time Series Model Analysis Using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for E-wallet Transactions during a Pandemic

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Abstract

Financial transaction activities during the pandemic are increasingly shifting to digital media due to the call to reduce direct interaction so that customers tend to choose online banking. One of the services that provide new convenience in transactions is e-wallet. The use of e-wallet can be accessed easily via the internet, this can create a positive impact for economic stability after the Covid-19 pandemic. Based on data, users of e-wallet services in Indonesia during the pandemic experienced a fairly large increase. Several types of e-wallet can be analyzed for time series models, so that they can help project e-wallet transactions in the post-pandemic future. The method for obtaining the time series model is using the Autocorrelation Function (ACF) and Partial Autocorrelation Function. The time series data used is a transaction from an e-wallet in Indonesia on May 1, 2020 – August 31, 2020. This research was assisted by R software. Based on the identification of the time series model using the ACF and PACF plots on the E-Wallet transaction data, then suitable for AR(1) models. This is expected to provide a projected mapping of E-Wallet transactions during the pandemic. Furthermore, the time series model can be continued to predict future E-Wallet transactions. If you get a forecast for E-Wallet transaction data, it can be used to develop the post-pandemic digital economy axis.

Keywords: E-wallet, time series, ACF, PACF.

1. Introduction

Financial transaction activities during the pandemic are increasingly shifting to digital media due to the call to reduce direct interaction so that customers tend to choose online banking. In various regions affected by the pandemic, there has been a decline in traditional banking transactions and as a result, the increase in E-banking platforms is observed to be at a critical point in adaptation to changes in new normal activities (Yanagawa, 2020). These external factors encourage innovation in the banking sector. Banks risk being left behind in responding to the current state of technology (Mishra, 2020). Banking companies need to ensure that they keep pace and take significant steps to compete effectively with financial institutions at the forefront of technology as well as digital giants and fintech companies. The introduction of next-generation technologies, such as application programming interfaces (API), artificial intelligence (AI), machine learning and robotics, is required to be ready to bring the customer experience to a new level of convenience (Carbó-Valverde et al., 2020). One of the services that provide new convenience in transactions is e-wallet.

The use of e-wallet can be accessed easily via the internet, this can create a positive impact for economic stability after the Covid-19 pandemic. This can move the wheels of the community's economy, through online shopping and the use of e-wallet among the public. Based on data from Redseer (2020) the use of a number of digital services in Indonesia has increased during the Covid-19 pandemic. The first position is occupied by e-commerce and the second position is occupied by digital wallets which increased by 65%. This proves that digital wallets are increasingly becoming an option for the Indonesian people in transacting as can be seen in Figure 1.

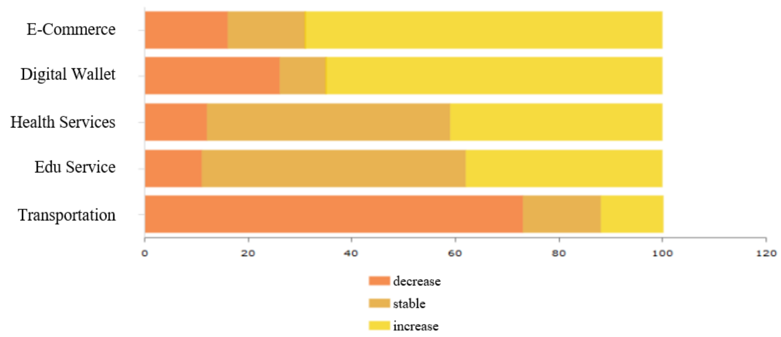

Figure 1. Use of Digital Services in Indonesia during the 2020 Covid-19 Pandemic

Based on data from the increasing number of e-wallet service users in Indonesia. There are several forms of e-wallet that have a large scale, such as GoPay, OVO, Tokopedia, and Bukalapak. Several types of e-wallets can be analyzed for time series models, so that they can help project e-wallet transactions in the post-pandemic future. The method for obtaining the time series model is using the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF).

2. Literature Review

2.1. Financial Technology

Financial technology or often referred to as fintechs, shows the combination of financial services with new things in technology. A technology related to building systems that create, value and process financial products such as bonds, stocks, contracts and money is the definition of financial technology (Freedman, 2006). While another definition is, an industry that moves very quickly and dynamically where there are many different business models (Dorfleitner et al., 2017). It can be concluded, financial technology is a new financial service model developed through innovation from information technology. Companies in the fintechs industry have almost everything in common, according to Dorfleitner et al. (2017), companies in the fintechs industry can be divided into four main segments according to different business models, namely: 1. Financing; 2. Asset Management; 3. Payment; 4. Other Fintechs.

2.2. E-Wallet

Electronic money was created as a means of payment that can be used in transactions without the need for money in physical form. Electronic money has two types of storage media, namely server-based and chip-based storage. Chip-based electronic money, in the form of cards that have chips embedded in them. Meanwhile, the form of server-based electronic money is electronic money which in the process of its use requires a connection with the issuing server first, this form is often called an electronic wallet (e-wallet). E-wallet is defined as a digital currency, where there is convenience in shopping without the need to carry money in physical form (non-cash) and can be channeled when carrying out other activities (Megadewandanu, Suyoto, & Pranowo, 2016). Meanwhile, according to Kuganathan & Wikramanayake (2014) e-wallet or what is often referred to as a mobile wallet is a payment service that is operated under financial regulations and is carried out via mobile devices. Ewallet is said to be the latest type of e-commerce payment that allows users to make transactions and orders online within the application (Sharma et al., 2018).

3. Materials and Methods

3.1. Materials

In this study, identification of time series models was carried out, from one of e-wallet in Indonesia during the pandemic. The time series data used is the e-wallet transaction on May 1, 2020 - August 31, 2020. This research was assisted by the R software.

3.2. Methods

The methods used to analyze the model are Autocorrelation Function (ACF) and Patial Autocorrelation Function (PACF). This research is assisted by R software. The steps are as follows:

1. Time series plot, the purpose of this time series plot is to see the stationarity of the data, whether the data is stationary either in the mean or in the variance;
2. If the data is not stationary, differencing is performed;

3. After the data stationary data is reached, the ACF and PACF plots are carried out;
4. ACF and PACF plots can be identified by the characters of the plots;
5. The time series model is determined based on the identification of the ACF and PACF plots.

3.2.1. Box Jenkins Method

The Box Jenkins method is one of the time series model forecasting techniques that is only based on the past behavior (historical) of the predicted variable. The Box Jenkins method consists of several techniques, namely: (1) Autoregressive (Autoregressive/AR) Model; (2) Moving Average (MA) Model (3) Moving Average Autoregressive Model (ARMA) (4) Moving Average Integration Autoregressive Model (ARIMA) (Box, et al., 1994).

The Box Jenkins method has several assumptions, including: (1) The time series data to be analyzed and forecasted is stationary. Intuitively, data is said to be stationary if it fluctuates randomly around its mean value; (2) The mean value of the studied variables fluctuates around a fixed zero value (William, 1989).

3.2.2. Autoregressive Model

The autoregressive (AR) model shows Y_t as a linear function of the previous actual Y_t number, or expressed in the formula:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots + b_p Y_{t-p} e_t \tag{1}$$

where: Y_t = dependent variable; Y_{t-1}, Y_{t-2},…, Y_{t-p} = independent variable; b_0, b_1,…, b_p = regression coefficient (lag of dependent variable); e = residuals; p = AR level or autoregressive degree.

There are several classifications of AR models: (1) Random model (white noise series), namely a model in which a time series data Y_t, contains an element of arithmetic mean (μ) and an element of random error (e_t), which is free from autocorrelation problems. Box Jenkins ARIMA notation (0,0,0) with the formula: $Y_t = \mu + e_t$. (2) p-level autoregressive model, meaning that the model contains autocorrelation between Y_t and Y_{t-p}. The formula is $Y_t = \mu + Y_{t-1} + e_t$ with Box Jenkins ARIMA notation (1, 0, 0) or $Y_t - Y_{t-1} = \mu + e_t$ with Box Jenkins ARIMA notation (1, 1, 0) (Wei, 2006).

3.2.3. Moving Average Model

The moving average (MA) model predicts the value of Y_t based on a combination of past linear errors (lag). The formula for the MA model is:

$$Y_t = w_0 + w_1 e_{t-1} - w_2 e_{t-2} - \cdots - w_q e_{t-q} + e_t \tag{2}$$

where: Y_t = dependent variable; e_{t-1}, e_{t-2}, ..., e_{t-q}= independent variable; w_0, $w_1, \dots, w_q$ = regression coefficient (lag of dependent variable); e = residuals; q = MA level or moving average degree.

The value of "q" in the moving average (MA) represents the MA model. For example, the MA (1) model or Box Jenkins ARIMA notation (0, 0, 1) has the formula $Y_t = w_0 + e_t - w_1 e_{t-1}$. While the MA model (2) or Box Jenkins ARIMA notation (0, 0, 2) is $Y_t = w_0 + e_t - w_1 e_{t-1} + w_2 e_{t-2}$ (Banhi, 2006).

3.2.4. Autoregressive Moving Average Model

The AR (p) and MA (q) models can be combined into a model known as the Autoregressive Moving Average (ARMA), so it has the assumption that the current period data is influenced by the data in the previous period and the residual value in the previous period (Prapanna, 2014). ARMA model with order p and q is written ARMA(p, q) or ARIMA($p, 0, q$) which has the following equation:

$$Y_t = w_0 + w_1 e_{t-1} - w_2 e_{t-2} - \cdots - w_q e_{t-q} + e_t \tag{3}$$

where: Y_t = dependent variable; = constant; b_0, b_1, …, b_p = AR coefficient; w_1, w_2,..., w_q = coefficient of MA parameter; Y_{t-1}, Y_{t-2}, Y_{t-p} = independent variable; e_{t-1}, e_{t-2}, e_{t-q} = lag of residual.

3.2.5. Autoregressive Integrated Moving Average Model

The model with stationary data through a differential process is called the autoregressive integrated moving average (ARIMA) model. The ARIMA model can be written with the equation.

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots + b_p Y_{t-p} - w_1 e_{t-1} - w_2 e_{t-2} - \cdots - w_q e_{t-q} + e_t \tag{4}$$

The notation of the ARIMA model is determined by the number of periods of the independent variable, both from the previous value of the dependent variable and the residual value (Banhi, 2016; Prapanna, 2014). An example of writing an equation with ARIMA notation, namely:

- $Y_t = b_0 + b_1Y_{t-1} - w_1e_{t-1} + e_t \rightarrow$ ARIMA (1,0,1)
- $Y_t = b_0 + b_1Y_{t-1} + b_2Y_{t-2} - w_1e_{t-1} + e_t \rightarrow$ ARIMA (2,0,1)
- $Y_t = b_0 + b_1Y_{t-1} - w_1e_{t-1} - w_2e_{t-2} + e_t \rightarrow$ ARIMA (1,0,2)

3.2.6. Identify Time Series Models

The identification stage is carried out by preliminary data analysis for possible time series models. Simple identification is done visually by looking at the plot of the data, to see trends, seasonal components, non-stationarity in variance, and so on. This stage can also be used to see which data preprocessing techniques, which if needed, can be used to form stationary data. Some common data preprocessing techniques are removing outliers from the data, filtering data using certain statistical models/techniques, transforming data, performing difference operations, detrending (removing trends), deseasonalization (removing seasonal components), and others. Stationarity of the data can be seen from the form of the autocorrelation function estimator function (ACF sample/Autocorrelation function) and partial autocorrelation function estimator (PACF/Partial ACF sample), or by performing unit root tests on the data.

The identification of the time series model is carried out in several steps, namely: (1) Determining whether a time series data is stationary (the average value does not shift over time). If the data is not stationary, then the data conversion must be done (to be stationary) using a differential process. (2) Determine the model to be used. Determination of the model is done by comparing the ACF and PACF coefficients from the data with the ARIMA model to determine the most suitable model.

3.2.7. Differential Process

The differential process is used to convert non-stationary data into stationary data (requirement for ARIMA implementation). Differential notation 1, defined as:

$$X' = X_t - X_{t-1} \tag{5}$$

Meanwhile, if the first differential has not made the data stationary, then differential notation 2 can be used, which is defined as follows:

$$X'' = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2}) \tag{6}$$

3.2.8. Analysis of ACF and PACF in the Identification of the Box Jenkins Model

The order of the model can be seen as ACF, namely the magnitude of the relationship value between observations at time t and the previous time, namely:

$$r_k = corr(Y_t, Y_{t-k}) = \frac{\sum_{t=1}^{n-k}(Y_t-\bar{Y})(Y_{t+k}-\bar{Y})}{\sum_{t=1}^{n}(Y_t-\bar{Y})^2} \tag{7}$$

Then the correlation coefficient needs to be tested to determine whether the value is significantly different from zero or not.

Using the formula $se_{rk} = \frac{1}{\sqrt{n}}$, then PACF (Partial Autocorrelation Function) which is a partial correlation between observations at time t and previous times. PACF shows the correlation between Y_t and Y_{t-k}, ignoring the independence $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}$, so Y_t is considered as a constant, $Y_t = y_t,\ t = t+1, t+2, \dots, t+k-1$.

$$r_{kk} = corr(Y_t, Y_{t-k} \mid Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}) \tag{7}$$

4. Results and Discussion

4.1. Identification of E-wallet Transaction Data

The e-wallet transaction data used in this study is one of the e-wallet in Indonesia. The e-wallet service provider has a large number of customers with a wide area coverage. The e-wallet transactions taken are data during the pandemic. The time series data was obtained on May 1, 2020 – August 31, 2020. The e-wallet transaction data can be seen in Figure 2.

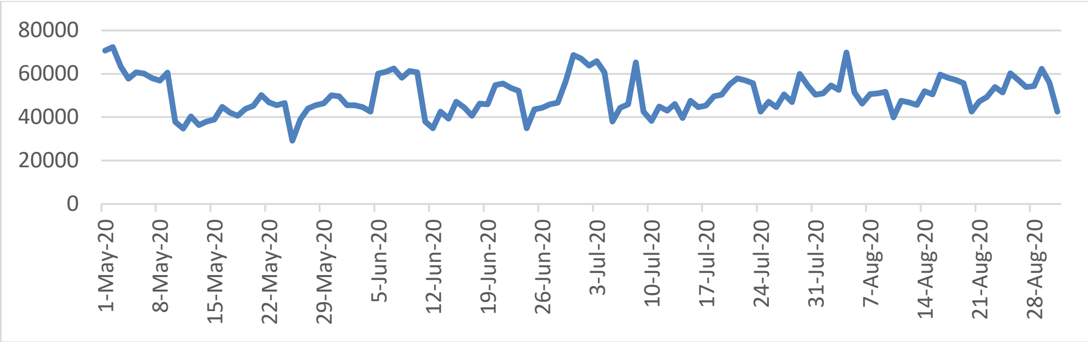

Figure 2. Transaction Data from One of E-wallet in Indonesia

Based on Figure 2, it can be seen that the average and variance are constant, so the time series data is said to be stationary. Overall, it can still be said that the mean and variance are constant. Based on this, the time series data for e-wallet transactions can be continued for the ACF and PACF plots because they are stationary.

4.2. ACF Plot of E-wallet Transaction Data

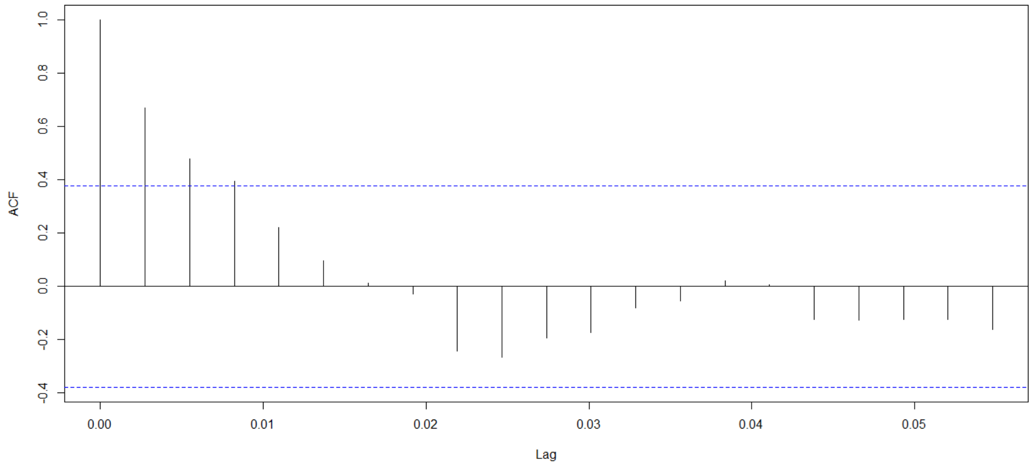

Figure 3. ACF Plot of E-wallet Transaction Data

Based on Figure 3, the ACF plot of the e-wallet transaction data shows the dies down plot. The shape of the dies down is commonly referred to as a graph that follows a sine wave. The ACF plot indicates that the time series data follows the AR or autoregressive model. The AR time series model is obtained if the ACF plot decays towards zero or follows a sine wave pattern (dies down). Next, the e-wallet transaction data needs to be depicted in the PACF plot graph. The PACF plot will help determine the p value in AR(p).

4.3. PACF Plot of E-wallet Transaction Data

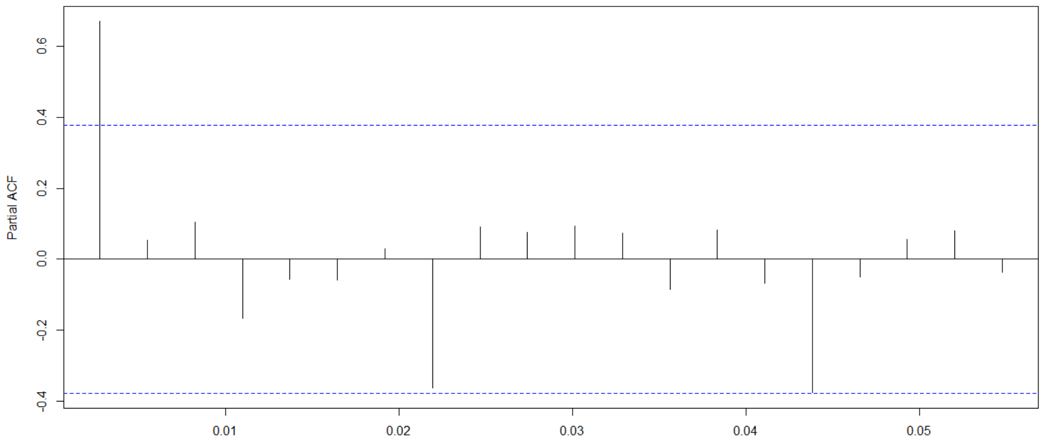

Figure 4. PACF Plot of E-wallet Transaction Data

Based on Figure 4, the PACF plot of the e-wallet transaction data shows the form of a plot that is cut off immediately to zero after lag p. The lag p in question is lag 1, this is because the PACF plot is interrupted immediately when the graph passes lag 1. The PACF plot indicates that the time series data follows the AR(1) model.

The AR(1) time series model is obtained because the ACF plot decreases towards zero rapidly (exponentially) or follows a sine wave (dies down). While the PACF plot shows results that are truncated after the 1st lag. So, the time series model that will be used is AR (1).

5. Conclussion

Based on the results of the identification of the time series model using the ACF and PACF plots on the E-Wallet transaction data, it is suitable for the AR(1) model. This is expected to provide projections for mapping E-Wallet transactions during the pandemic. Furthermore, the time series model can be continued to predict future E-Wallet transactions. If you get the forecast for the E-Wallet transaction data, it can be used to develop the post-pandemic digital economy axis. That is to see the opportunity for E-Wallet transactions as the main transaction, in order to reduce the use of physical means of exchange. So that the spread of the pandemic can be suppressed.

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