

Forecasting The Number of Aircraft Passengers Arriving Through Soekarno-Hatta Airport Using Arima Model

Windi Marnizal Putri^{1*}, Fauziah Nur Fahirah Suding²

^{1,2} Study Program of Actuarial Science, School of Business, President University, 17550, Indonesia

*windi.putri@student.president.ac.id

Abstract— Soekarno-Hatta International Airport is well known as the busiest airport in Indonesia with the number of airplane passengers normally grow from year to year. In 2010, there were more than 43 million passengers, and had increased up to 62.4 million over the year 2011. Risk of overcapacity became an issue. Thus, in the following year, the airport was planned for an expansion. Predicting the frequency of passengers can be helpful for future planning and to improve airport facilities and policy. This research used Autoregressive Integrated Moving Average (ARIMA) to forecast the number of aircraft passengers. ARIMA (0,1,1) is the most suitable model used with MAPE 110%, the results is 2,405,205 passengers. Actual data and predictive data are not much different.

Keywords— ARIMA; Forecasting; MAPE; Soekarno-Hatta Airport

I. INTRODUCTION

In Indonesia, there are many types of airlines and airports that fly aircraft, one of which is Soekarno-Hatta International Airport. It was established in 1985 to replace Kemayoran International Airport. Then in 1991, it was expanded because it replaced the overcapacity Halim Perdana Kusuma International Airport and became the main airport that served the greater area of Jakarta. [1]

Passengers traffic growth has been dramatically increase. In 2010, The airport reported that there were around 43,7 millions passengers and 338,711 aircraft movement. By 2011, air passengers reached 62.4 millions. [2] The overcapacity became large issue, consequently expansion of the airport was planned to overcome the crowded since it affected the service and time management. Predicting the frequency of people take flight could also be one solution since the results can be used for future planning in improving airport capacity and facilities. [3]

Many studies have been carried out in forecasting the number of passengers. Fahik and Jatipaningrum (2021) compare two methods, Holt-Winters Exponential Smoothing and Seasonal ARIMA in predicting total passengers in Soekarno Hatta International Airport. Holt-Winters Exponential Smoothing produced smaller MAPE value (4.407%) than Seasonal ARIMA (5.306%). Predicting result for March 2020, is estimated to 732,129 people. [4]

Another study from Hasanah (2019), she also analyzed number of airport passengers in Juanda International Airport. By comparing three methods, ARIMA, Regression Time Series and TBATS, resulting ARIMA to be best model. Kuswanto et al.,(2014), also estimated the frequency of passengers who travel through Juanda International Airport using ARIMA and Transfer Function. In this study, the writers also get ARIMA as the best method. [5]

From previous studies above, researchers were encouraging to use ARIMA to predict the frequency of aircraft passengers through Soekarno-Hatta International Airport in 2012-2016. Research result were expected to show that simple model can also produce good result. And as to be information for government and PT. Persero, to overcome the crowded such that it can improve facilities at the airport that will increase the value of Soekarno-Hatta airport.

II. LITERATURE REVIEW

A. Introduction to Time Series Analysis

A time series is a collection of observed data from a distribution with random variables that are recorded within a certain time but continuously, a time series is obtained. When observed continuously for some time interval. What distinguishes the time series is that the analysis can show how the variables change from time to time, or it can be called a variable which is an important factor because it will show a picture of the data that corresponds to the data points. [6]

B. Stochastic

Process A stochastic processor also called a random process is a random variable that is indexed to several sets in mathematics. This process is the process of observing the times and determining the results where these results are called random variables. Time series of random variables is part of the stochastic process. Where to get the value of the book of Jesus using the formula, as follows:

- 1) *Mean* $\mu_t = E(X_t)$ (1)
- 2) *Variance* $Var(X_t) = t\sigma_e^2$ (2)
- 3) *Autocovariance* $\gamma_k = Cov(X_t, X_s)$ (3)
- 4) *Autocorrelation* $\rho_k = Corr(X_t, X_s)$ (4)

C. Stationary

Stationary is an important factor that must be present in time series analysis. Stationary can be known in several ways such as from graphs, correlograms, or through Root. Stationary itself means it is a time series of power that has a tendency to move on the average (mean). Stationary data usually crosses the horizontal axis when pulled, or its autocorrelation will decrease over a long period of time. [7]

D. Transformation of Time Series Analysis

In the transformation of time series analysis, there are differences in the forecasting of the two methods in the time series. This difference is a linear operation of the conditional expectation. There are two forecasting methods considered, namely:

- 1) *Non-stationary Time Series*
This time series can be used with the formula:
 $e_t = X_t - X_{t-1}$ (5)

- 2) *Stationary Time Series*
This Time Series can be used with the formula:
 $W_t = X_t - X_{t-1}$ (6)

- Or in its general form using the formula:
 $BX_t = X_{t-1}$ (7)

E. Formulas in Time Series Analysis

As previously mentioned, Time series has several important formulas that must be included in time series analysis, namely Autocovariance, Autocorrelation (ACF) functions, Partial Autocorrelation Functions (PACF). These three types of correlation are usually used in model specifications

- 1) *Autocovariance Function*
The definition of the Autocovariance function is [8]:

$$\rho_{xx}(t_1, t_2) = \frac{K_{xx}(t_1, t_2)}{\sigma_{t_1} \cdot \sigma_{t_2}} = \frac{E[(X_{t_1} - \mu_{t_1})]}{\sigma_{t_1} \cdot \sigma_{t_2}} \quad (8)$$

And can also be denoted by:

$$\gamma_k = Cov(X_t, X_s) \text{ for } k = 0, \pm 1, \pm 2, \pm 3, \dots \quad (9)$$

The set of values $\gamma_{k,k} = 0, 1, 2, \dots$ or $\gamma_0 = \sigma_y^2$ is a function symbol of the Autocovarian Function, where [9]:

$$Covv(X_t, X_s) = E(X_t - \mu_t)(X_t - \mu_s) = E(X_t, X_{t-s}) - \mu_t \cdot \mu_s$$

- 2) *Autocerrelation Function (ACF)*

Autocorrelation function is usually used to find stationarity of analysis time series data. In general, the function of Autocorrelation is to define how similar the data is to the time version itself. The random process $X(t)$ is also called $E[X^2(t)] < \infty$ for each $t \in T$ if it is second order. The autocorrelation functions of $X(t)$ and $X(s)$ are denoted by $R_{xx}(t, s)$ and are also denoted by:

$$R_{xx}(t, s) = E[X(t)X(s)] = E[X(s)X(t)] = R_{xx}(s, t) \tag{9}$$

$$R_{xx}(t, t) = E[X^2(t)]$$

Or you can also use the formula:

$$\rho_k = \text{Corr}(X_t, X_s) \text{ for } k = 0, \pm 1, \pm 2, \pm 3, \dots \tag{10}$$

Where:

$$\text{Corr}(X_t, X_s) = \frac{\text{Cov}(X_t, X_s)}{\sqrt{\text{Var}(X_t)\text{Var}(X_s)}} = \frac{\gamma_k}{\gamma_0} \tag{11}$$

3) Partial Autocorrelation Function

Partial Autocorrelation Function is the correlation between two variables to calculate the value of a set of variables.

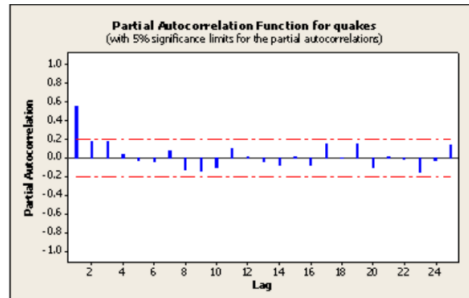


Figure. 1 Partial Autocorrelation Function

Partial Autocorrelation Function is denoted by [10] :

$$\frac{\text{Cov}(y, x_3|x_1, x_2)}{\sqrt{\text{Var}(y|x_1, x_2)\text{Var}(x_3|x_1, x_2)}} \tag{12}$$

$$y = \beta_0 + \beta_1 x^2 \text{ and } y = \beta_0 + \beta_1 + \beta_2 x^2 \tag{13}$$

Or

$$\phi_{kk} = \text{Corr}(X_t, X_{t-k}|X_{t-k}, X_{t-2}, \dots, X_{t-k+1}) \tag{16}$$

III. ANALYSIS AND RESULTS

A. Data Preparation

The data used in this paper is data on the number of passengers arriving through Soekarno-Hatta International Airport from January 2012 to December 2016.

TABLE 1
THE NUMBER OF PASSENGERS ARRIVING BY SOEKARNO-HATTA INTERNATIONAL AIRPORT

mm/yyyy	Data	mm/yyyy	Data
Jan-12	2314964	Jul-14	2092201
Feb-12	2127022	Aug-14	2810608
Mar-12	2362070	Sept-14	2296555
Apr-12	2341738	Pkt-14	2382573
May-12	2409964	Nov-14	2306529
Jun-12	1978000	Des-14	2492669
Jul-12	2384206	Jan-15	2196439
Aug-12	2472378	Feb-15	1959646
Sep-12	2421433	Mar-15	2103921
Okt-12	2405838	Apr-15	2104874

Nov-12	2346410	May-15	2293224
Dec-12	2483418	Jun-15	2171041
Jan-13	2374483	Jul-15	2550866
Feb-13	2112179	Aug-15	2339590
Mar-13	2481657	Sep-15	2067674
Apr-13	2406460	Okt-15	2240216
May-13	2545296	Nov-15	2250089
Jun-13	2764786	Des-15	2478472
Jul-13	2394358	Jan-16	2304570
Aug-13	2772952	Feb-16	2072698
Sep-13	2449839	Mar-16	2278964
Okt-13	2546954	Apr-16	2275596
Nov-13	2450975	May-16	2581790
Des-13	2543140	Jun-16	2126278
Jan-14	2481027	Jul-16	2856824
Feb-14	1986114	Aug-16	2466109
Mar-14	2190455	Sep-16	2318798
Apr-14	2141703	Okt-16	2331367
May-14	2386400	Nov-16	2293547
Jun-14	2507504	Des-16	2654623

Source : bps.go.id

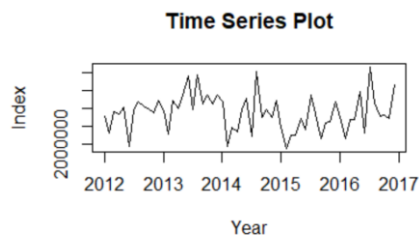


Figure. 2 Training Data

B. Stationary

Our data is said to be stationary if the p value is less than 0.05. We can check the stationarity of the data by using the ADF test in R. According to the results, the p-value is 0.1599 which is greater than 0.05, thus data is not stationary. Therefore, we have to differencing the data until it is < 0.05 or becomes stationary. After differencing, the p-value of the data finally became smaller than 0.05, which means that the data we have is stationary. The following is a plot of Time Series, Autocorrelation Function, and Partial Autocorrelation Function from data on the number of passengers arriving through Soekarno-Hatta International Airport in 2012-2016.

C. $AR(p)$ and $MA(q)$

Orders of AR and MA can be determine using PACF for Order p and ACF for Order q.

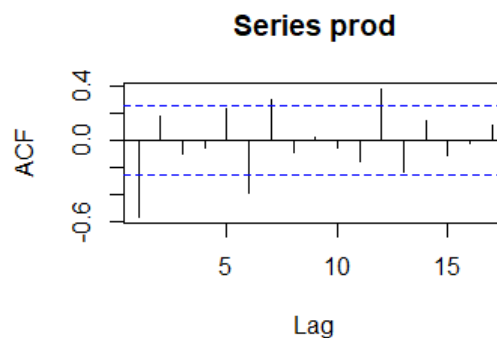


Figure. 3 ACF

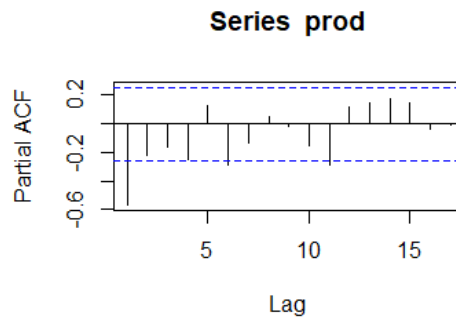


Figure. 4 Partical ACF (PACF)

It can be seen that the cut off for PACF and ACF are both at lag time 1. Thus, the AR order, namely p , is 1 and the MA order, q , is 1.

D. Model Specification

Here are the model specifications for the ARIMA model, so there will be 7 models with d equal to 1.

TABLE 2
ARIMA MODEL SPECIFICATION

Model ARIMA	P	d	q
ARIMA(1,1,0)	1	1	0
ARIMA(0,1,0)	0	1	0
ARIMA(1,1,1)	1	1	1
ARIMA(0,1,1)	0	1	1

E. Parameter Estimation

The following are the parameter estimates for all models. We can determine it after we know the ARIMA model and we can determine the estimated coefficients consisting of AR1, AR2, AR3, Log likelihood, MSE, RMSE, MAE, MAPE, and AIC which will be considered for forecasting later.

TABLE 3
ESTIMATION MODEL ARIMA DARI AR1, MA1, LOG LIKELIHOOD, MSE, RMSE, MAE, MAPE, AND AIC
Coefficient Estimation Result

Model ARIMA	AR1	MA1	Log Likelihood	MSE	RMSE	MAE	MAPE	AIC
ARIMA (1,1,0)	-0.5797		-810.29	66766845170	258392.8118	66766654436	89%	1622.58
ARIMA (0,1,0)			-822.11	65191765260	255326.7813	65191588517	86%	1644.21
ARIMA (1,1,1)	-0.0661	-0.8063	-805.94	84079744816	289965.0752	84079507306	108%	1615.87
ARIMA (0,1,1)		-0.8421	-806	87123131570	295166.2778	87122888062	110%	1614

F. Residual Analysis

From the residual analysis, the p-value must be more than 0.05 to get the best model for our data. To determine the best model, we can use the Saphiro test and Ljung's test. The model that passes the test will be the best model.

TABLE 4
Residuals Analysis

Model ARIMA	Shapiro Test	Ljung Test	AIC
ARIMA(1,1,0)	0.3765	0.2736	1622.58
ARIMA(0,1,0)	0.4188	6.497e-06	1644.21
ARIMA(1,1,1)	0.8213	0.9603	1615.87
ARIMA(0,1,1)	0.7587	0.7101	1614

G. Best Model Evaluation

After testing the model through the Shapiro and Ljung-Box tests, from the forecasting results we can see which model is close to the actual data, and in this case the model that is suitable for forecasting is Model 4, namely ARIMA(0,1,1).

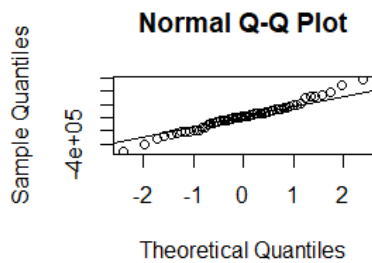


Figure 5 Model 4 Residual Plot

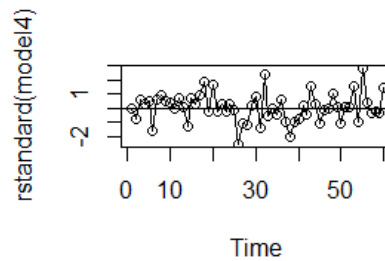


Figure 6 Model 4 Standardised Residual Plot

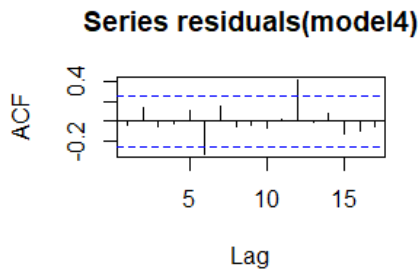


Figure 7 Model 4 ACF Residual

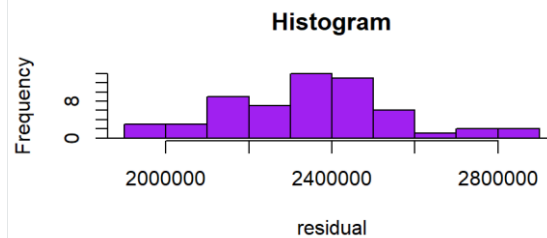


Figure 8 Model 4 Histogram

H. Forecasting

The following are the parameter estimates for all models. We can determine it after we know the ARIMA model and we can determine the estimated coefficients consisting of AR1, AR2, MA1, Log likelihood, and AIC which will be considered for forecasting later.

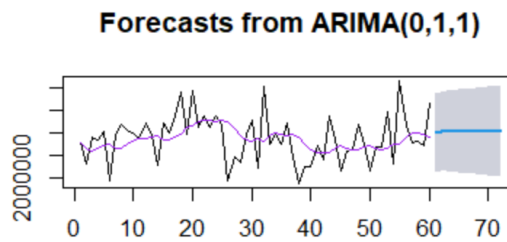


Figure 9 Model 4 Forecast

I. Comparison Between Actual and Forecast Data

The following is a comparison table for forecast data training with test data (12 final actual data).

TABLE 5
TABLE OF ACTUAL AND FORECAST DATA

Year	Month	Point Forecast	Lower Boundary	Upper Boundary	Actual Data
2017	Januari	2405205	1872161	2938248	2611736
2017	Februari	2405205	1865560	2944849	2160303
2017	Maret	2405205	1859039	2951370	2506223
2017	April	2405205	1852595	2957814	2459888
2017	Mei	2405205	1846225	2964184	2663541
2017	Juni	2405205	1839927	2970482	2201103
2017	Juli	2405205	1833699	2976710	3158315
2017	Agustus	2405205	1827537	2982872	2627000
2017	September	2405205	1821441	2988968	2585256
2017	Oktober	2405205	1815408	2995001	2580263
2017	November	2405205	1809435	3000974	2614908
2017	Desember	2405205	1803522	3006887	2718013

IV. CONCLUSION

The data used in this paper was taken from bps website. After processing and analyzing, the data on the number of passengers who came through Soekarno-Hatta Airport in 2012-2016 used the ARIMA model (0,1,1) which is the best data from the smallest number of AIC after the Shapiro Test and Ljung Boox. Results show that the point forecast during 2017 is 2405205 people, which are close to actual data. Using 90% confidence interval, we can conclude that the actual data values are within estimation interval.

REFERENCES

- [1] Wikipedia, "Bandar Udara Internasional Soekarno-Hatta," *en.wikipedia.org*, 2022. Accessed on: August 28, 2022, Available: https://id.wikipedia.org/wiki/Bandar_Udara_Internasional_Soekarno%E2%80%93Hatta
- [2] Badan Pusat Statistik, "Jumlah Penumpang Pesawat Udara yang Berangkat dan Datang Melalui Pelabuhan Udara Soekarno-Hatta 2018-2021," BPS, Jakarta. Accessed on: August 28, 2022, Available: <https://jakarta.bps.go.id/indicator/17/309/1/jumlah-penumpang-pesawat-udara-yang-berangkat-dan-datang-melalui-pelabuhan-udara-soekarno-hatta.html>
- [3] H. Kuswanti, Suhartono, and A.M. Huda, "Forecasting The Frequency Of Domestic Air Passengers At Juanda Airport Using ARIMA and Transfer Function As A Basis For Future Development Of Airport Scenario," *Jurnal Tata Kota dan Daerah*, vol. 6, No. 1, 2014.
- [4] D.S. Fahik and M.T Jatipaningrum, "Peramalan Jumlah Penumpang Penerbangan International Di Bandar Udara Soekarno-Hatta dengan Metode Holt-Winter Exponential Smoothing dan Seasonal ARIMA," *Jurnal Statistika dan Industri dan Komputasi*, vol. 6, No.1, 2021, pp.77-87
- [5] S. Hasanah, "Peramalan Jumlah Penumpang di Bandara International Juanda Menggunakan Metode ARIMA Regresi Time Series," *TBATS. JUSTEK : Jurnal Sains dan Teknologi*, Vol 2, No.1 , 2019, pp. 29-37, ISSN 2620-5475, <http://journal.ummat.ac.id/index.php/justek>
- [6] Tableau, "Time Series Analysis: Definition, Types, Techniques, and When It's Used," *tableau.com*, 2003. Accessed on: August 28, 2022, Available: <https://www.tableau.com/learn/articles/time-series-analysis#:~:text=Time%20series%20analysis%20is%20a,data%20points%20intermittently%20or%20randomly>.
- [7] T. J. Long, "Uji Stasioneritas Data Time Series," *jagostat.com*. Accessed on: August 28, 2022, Available: [https://jagostat.com/analisis-time-series/uji-stasioneritas-data-time-series#:~:text=%2DPerron%20Test\),Stasioneritas%20merupakan%20konsep%20penting%20dalam%20analisis%20time%20series.,rata%20dan%20variannya%20konstan](https://jagostat.com/analisis-time-series/uji-stasioneritas-data-time-series#:~:text=%2DPerron%20Test),Stasioneritas%20merupakan%20konsep%20penting%20dalam%20analisis%20time%20series.,rata%20dan%20variannya%20konstan).
- [8] Wikipedia, "Autocovariance," *en.wikipedia.org*, 2021. ccessed on: August 28, 2022, Available: <https://en.wikipedia.org/wiki/Autocovariance#:~:text=In%20probability%20theory%20and%20statistics,of%20the%20process%20in%20question>.
- [9] Science Direct, "Autocorrelation Function," *ScienceDirect*, 2001. Accessed on: August 28, 2022, Available: <https://www.sciencedirect.com/topics/mathematics/autocorrelation-function#:~:text=Introduction%20to%20Random%20Processes&text=Basically%20the%20autocorrelation%20function%20defines,for%20each%20t%20E%28%88%88%20T>.
- [10] PennState, "Partial Autocorrelation Function (PACF)," The Pennsylvania State University , 2022. Accessed on: August 28, 2022, Available: <https://online.stat.psu.edu/stat510/lesson/2/2.2>