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THE EFFECT OF ENSEMBLE AVERAGING METHOD ON RAINFALL FORECASTING IN JAKARTA USING ARIMA AND ARIMAX

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ABSTRACT

This research discusses rainfall modeling using ARIMA and ARIMAX models in Jakarta. This is important because rainfall forecasting in Jakarta has a significant impact on flooding and infrastructure. The focus of this research is on significant ARIMA and ARIMAX models, which are then subtotaled using ensemble averaging. Humidity and temperature variables are of particular interest in ARIMAX modeling due to their high correlation with rainfall. This quantitative research uses secondary data analysis from Tanjung Priok and Kemayoran Stations through the BMKG website, from July 2018 to June 2023. The results obtained at Tanjung Priok Station there are five significant ARIMA models and three significant ARIMAX models. While at Kemayoran Station there are 6 significant ARIMA models and two significant ARIMAX models. After using the ensemble averaging method on both ARIMA and ARIMAX models, the resulting SMAPE value is not better than the best ARIMA or ARIMAX models at both stations. Of all the models performed, the best model in forecasting with the smallest SMAPE is ARIMAX (0,0,1) at Tanjung Priok Station which is 37.83% and at Kemayoran Station which is 27.59%. This research provides new insights and significant contributions in understanding and developing rainfall forecasting in Jakarta using the ensemble averaging method.

Keywords: ARIMA, ARIMAX, Ensemble Averaging, Rainfall

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PRELIMINARY

Rainfall has a wide-ranging impact on people's lives in Jakarta. Along with rapid urban growth, heavy rainfall can cause serious problems, especially in terms of flooding. Flooding can cause huge losses, such as damage to infrastructure and threats to the safety of residents. This makes it important to perform accurate rainfall forecasting (Annas & Kasim, 2019). One of the most frequently used forecasting methods in rainfall forecasting is ARIMA (Autoregressive Integrated Moving Average) and ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variable). Several previous studies related to rainfall forecasting and topics related to ARIMA or ARIMAX methods have been conducted. Among others, research related to oil export forecasting using ARIMA shows

16 significant models, with ARIMA (5,1,3) having the lowest MAPE of 8.142% (Sinaga et al., 2023). Research was also conducted on rainfall modeling in Bogor, showing the optimal ARIMA (1,1,1), ARIMA (1,1,0), and ARIMA (3,1,0) models (Maulana, 2018). In addition, there is research that focuses on the ARIMAX model to forecast rainfall in Bali, producing a model with a MAPE value of 15.79% (Nisa et al., 2021). Another research on the ARIMAX method in Pangkalpinang shows that the ARIMAX (0,1,3) model is suitable for monthly data with maximum wind speed variables (Amelia et al., 2021).

Forecasting often shows that when modeling rainfall using ARIMA or ARIMAX methods, there is more than one significant model (Setiyowati et al., 2018). This makes the ensemble averaging method appear as a strategic step to overcome these challenges. The use of the ensemble averaging method, which involves a combination of significant model outputs from several models, can reduce uncertainty and improve forecasting accuracy. The main reason for using this method in the context of ARIMA and ARIMAX is to utilize the advantages of each significant model, so as to produce forecasts that may be more reliable (Rahayu et al., 2022).

In this regard, the application of ensemble methods has also been applied in various forecasting contexts. For example, in some previous research has been done by combining other methods, among others: Previous research has combined other methods such as the comparison of ARIMA Box Jenkins forecasting with ARIMA ensemble (Tasyah et al., 2023). Other research on economic growth forecasting involves 3 methods Single MA, Single Exponential and ensemble (Fransiska, 2022). And finally another study, comparing ARIMA, GSTAR, ensemble stacking, and ensemble averaging found that the ensemble method produced the lowest RMSE value in rainfall forecasting (Anggraeni et al., 2018).

Thus the above research findings provide a strong theoretical basis for exploring the influence of ensemble averaging methods in the context of rainfall forecasting in Jakarta, with the complexity of weather and uncertainty that exists in Jakarta using ARIMA and ARIMAX methods. The novelty of this research lies in rainfall forecasting using the ensemble averaging method, especially with the ARIMA or ARIMAX method, is still fairly minimal, especially in Jakarta which is prone to flooding. This is a motivation for the author to study the effect of the ensemble averaging method on rainfall modeling in Jakarta using ARIMA and ARIMAX models, with the hope of providing new insights and significant contributions in understanding and developing accurate and more reliable rainfall forecasting in the Jakarta area as one of the efforts to mitigate flood disasters and urban infrastructure.

METHODS

This research uses R Studio for quantitative analysis with secondary data obtained from the Meteorology, Climatology and Geophysics Agency (BMKG) website. With monthly rainfall data in Jakarta represented by two stations namely Tanjung Priok Station and Kemayoran Station for 5 years (July 2018 to June 2023). The exogenous variables in ARIMAX modeling are humidity and air temperature. The data is divided into training (90% from July 2018 to December 2022) and testing (10% from January to June 2023). The training data is used to determine significant ARIMA and ARIMAX models. SMAPE was evaluated on the testing data for both models and ensemble averaging.

Before estimating the model parameters with Ordinary Least Square (OLS), the rainfall data were explored to handle zero values to overcome the stationarity (Tantika et al., 2018). The next stage is to identify the stationarity of the data with respect to variance using the Box-Cox test with a rank transformation of the response and testing for mean stationarity using the Augmented Dickey-Fuller (ADF) test (Matulessy, 2019). If the data is not stationary in the mean, differencing is performed. After the data is stationary in both variance and mean, ARIMA modeling is performed first (Pitaloka et al., 2019).

ARIMA modeling begins with the model identification stage based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) values (Woodward et al., 2020). The next step is parameter determination and significance testing is carried out. Models in which all model parameters are significant are tested for ARIMA model diagnostics using the Jarque-Bera test to see normality in the residuals and the Ljung-Box test to see autocorrelation in the model residuals (Lailiyah & Manuharawati, 2018). Models that fulfill the ARIMA assumptions are used to determine the accuracy of the model using the Symmetric Mean Absolute Percentage Error (SMAPE) value (Suryani et al., 2018).

The SMAPE value is calculated with the following formula

$$\text{SMAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \widehat{Y}_t|}{(|Y_t| + |\widehat{Y}_t|)/2} \times 100\%$$

With,

Y_t : Represents the actual value at time t

$\widehat{Y}_t$: Is the predicted value of forecasting at time t

n : Represents the number of observations available

The next stage is ARIMAX modeling starting with looking at the correlation of exogenous variables and rainfall using the Pearson correlation test, this test is carried out to see a weak or strong relationship between the two variables (Ilmi et al., 2023). Furthermore, using the ARIMA model that has been significant in the previous stage, a parameter significance test is carried out for the ARIMAX model with the addition of exogenous variables (Elvina et al., 2023). Models with all significant model parameters are continued to the diagnostic test stage of the ARIMAX model (Ahmar et al., 2022). Models that fulfill all ARIMAX assumptions are used in the next stage, namely determining the SMAPE value of the testing data (Riestiansyah et al., 2022). After the formation of the ARIMA and ARIMAX models, forecasting is carried out with ensemble averaging, taking the average forecasting results from significant models (Syamsiah & Purwandani, 2021). With the ensemble averaging formula and flow as follows.

$$f = \left(\hat{y}_t^k\right), \frac{1}{N}\sum_{k=1}^{N}\hat{y}_t^k, \; t = 1, 2, \ldots, m$$

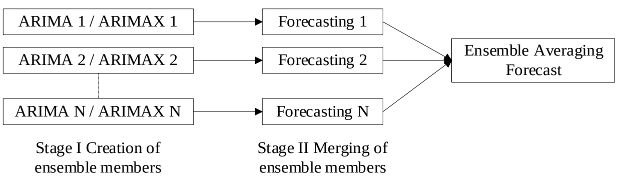

Figure 1. Ensemble Averaging Flowchart

Thus, the forecasting and SMAPE values for the ensemble averaging model are obtained. The results of all significant models (ARIMA, ARIMAX, and ensemble averaging) are compared to the SMAPE value. With the aim of seeing whether there is an influence between used.

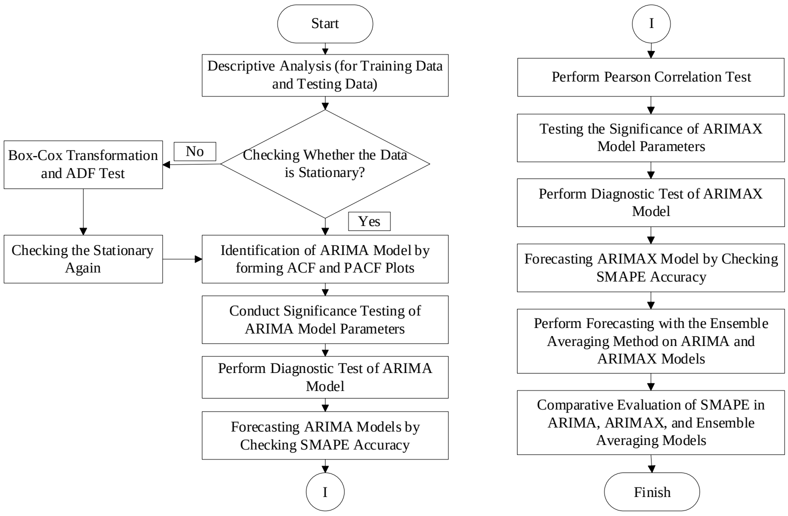

Figure 2. Research Flow

RESULT AND DISCUSSION

Data Stationary

The identification of stationarity can be seen through the plot of rainfall data at Tanjung Priok and Kemayoran stations.

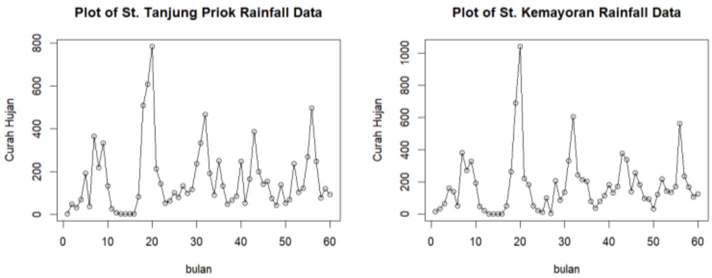

Figure 3. Trend Plot of Rainfall Data of Tanjung Priok and Kemayoran Stations

Based on the data plot in Figure 3, it shows fluctuations in rainfall values that are unstable and non-stationary with respect to variance at Tanjung Priok and Kemayoran stations. However, the presence of zero values in rainfall data becomes a problem when Box-Cox testing. In this case the Box-Cox test is performed once to test the stationarity of variance, with Box-Cox transformation of rainfall data at both stations using a power of 0,2.

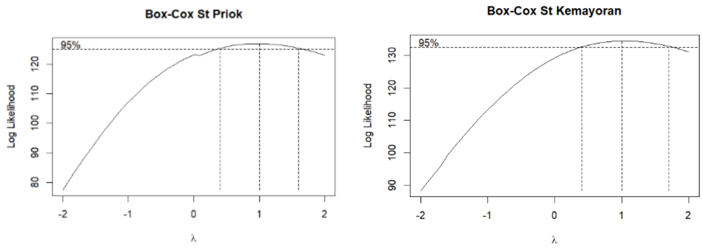

Figure 4. Box-Cox Testing Plot after Stationary on Rainfall Data

After checking the Box-Cox plot with lambda value, the resulting λ=1 is stationary in variance. Next, we check the stationarity of the data on the mean using the ADF test. The following are the ADF test results of rainfall, humidity, and temperature data in both regions

Table 1. ADF Test of Rainfall, Humidity, and Temperature Data

Station	Variables	P-value	Station	Variable	P-value
	Rainfall	0.010		Rainfall	0.010
Tanjung Priok	Humidity	0.010	Kemayoran	Humidity	0.010
	Temperature	0.015		Temperature	0.010

Based on Table 1 above, the P-value < 0.05, it can be concluded that the rainfall, humidity, and temperature variables are stationary at the mean.

ARIMA Modeling

After the data is stationary, ARIMA model identification is performed. Based on the ACF and PACF values as follows.

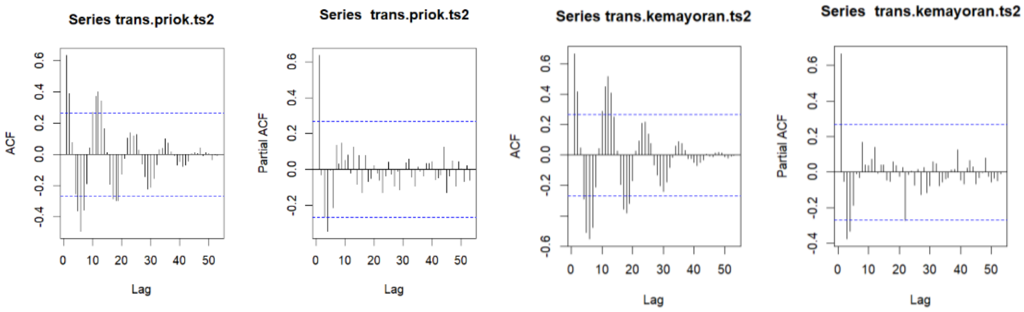

Figure 5. ACF and PACF Plots of Rainfall Variables

From the figure, it can be seen that in the rainfall data at Tanjung Priok Station, the ACF results cut-off at lags 1,2, and PACF cut-off at lags 1,3,4. Meanwhile, at Kemayoran Station, the ACF results cut-off at lags 1,2,4, and PACF cut-off at lags 1,3,4. The study only considers orders up to 4 because the higher the order, the modeling results tend to be less good. Thus, the ARIMA (p,d,q) model to be checked is ARIMA with orders (0,0,1), (0,0,2), (0,0,3), (0,0,4), (1,0,0), (1,0,1), (1,0,2), (1,0,3), (1,0,4), (2,0,0), (2,0,1), (2,0,2), (2,0,3), (2,0,4), (3,0,0), (3,0,1), (3,0,2), (3,0,3), (3,0,4), (4,0,0), (4,0,1), (4,0,2), (4,0,3), and (4,0,4).

Significance Test of ARIMA Model Parameters

Subsequently, the identified models were estimated and tested for parameter significance. Only models with all significant parameters are presented in Table 2.

Table 2. Significance Test Results of ARIMA Model Parameters

Tanjung Priok Station					Kemayoran Station				
Model	**Parameters**	**Coefficient**	**P-value**	**Significant**	**Model**	**Parameters**	**Coefficient**	**P-value**	**Significant**
(1,0,0)	AR (1)	0.6982	9.533×10^{-12}	Yes	(1,0,0)	AR (1)	0.6734	1.157×10^{-11}	Yes
(0,0,1)	MA (1)	0.6604	1.061×10^{-8}	Yes	(0,0,1)	MA (1)	0.4955	1.913×10^{-8}	Yes
(0,0,2)	MA (1)	0.5445	2.844×10^{-5}	Yes	(0,0,2)	MA (1)	0.5140	0.0004	Yes
	MA (2)	0.4565	0.0002	Yes		MA (2)	0.4383	0.0024	Yes
(2,0,2)	AR (1)	1.5995	2.2×10^{-16}	Yes	(0,0,3)	MA (1)	0.5942	9.158×10^{-6}	Yes
	AR (2)	-0.8508	2.2×10^{-16}	Yes		MA (2)	0.5796	4.250×10^{-7}	Yes
	MA (1)	-1.0287	3.238×10^{-7}	Yes		MA (3)	0.3224	0.00554	Yes
	MA (2)	0.4287	0.0043	Yes					
(3,0,2)	AR (1)	2.1577	2.2×10^{-16}	Yes	(0,0,4)	MA (1)	0.6383	2.609×10^{-6}	Yes
	AR (2)	-1.7373	1.347×10^{-7}	Yes		MA (2)	0.7097	1.965×10^{-7}	Yes
	AR (3)	0.4345	0.0161	Yes		MA (3)	0.6027	0.00015	Yes
	MA (1)	-1.5763	2.2×10^{-16}	Yes		MA (4)	0.3122	0.0186	Yes
	MA (2)	0.8341	3.925×10^{-1}	Yes	(2,0,2)	AR (1)	1.6277	2.2×10^{-16}	Yes
						AR (2)	-0.8928	2.2×10^{-16}	Yes
						MA (1)	-1.1205	8.578×10^{-11}	Yes
						MA (2)	-0.5034	4.914×10^{-5}	Yes

Based on parameter significance testing, it can be seen that the models with all significant parameters at Tanjung Priok Station are ARIMA (1,0,0), ARIMA (0,0,1), ARIMA (0,0,2), ARIMA (2,0,2), and ARIMA (3,0,2) models. Where as in Kemayoran Station is ARIMA (1,0,0), ARIMA (0,01), ARIMA (0,0,2), ARIMA (0,0,3), ARIMA (0,0,4), and ARIMA (2,0,2).

Jarque-Bera and Ljung-Box Diagnostic Test of ARIMA Model

The significant ARIMA models were tested diagnostically with the Jarque-Bera test and the Ljung-Box test. The results are shown in the following table.

Table 3. Normality Test with Jarque-Bera and Autocorrelation Test with Ljung-Box

Tanjung Priok Station			Kemayoran Station		
Model	**P-value Jarque-Bera Test**	**P-value Ljung-Box Test**	**Model**	**P-value Jarque-Bera Test**	**P-value Ljung-Box Test**
(1,0,0)	0.6054	0.9243	(1,0,0)	0.9496	0.8308
(0,0,1)	0.6505	0.5656	(0,0,1)	0.5239	0.0937
(0,0,2)	0.6677	0.5444	(0,0,2)	0.7072	0.2614
(2,0,2)	0.5898	0.7299	(0,0,3)	0.8343	0.7106
(3,0,2)	0.6114	0.4570	(0,0,4)	0.8631	0.9104
			(2,0,2)	0.5215	0.7649

Based on the results of the Jarque-Bera test and the Ljung-Box Test, the P-value > 0.05, indicates that the residuals of the model are normally distributed and free of autocorrelation.

ARIMAX Modeling

Correlation between variables was performed on the rainfall variable with exogenous variables. In this case, the correlation test results have a P-value < 0.05, indicating that there is a correlation between rainfall and humidity and temperature variables.

Significance Test of ARIMAX Model Parameters

In ARIMAX modeling, the ARIMA order is taken from the previous stage, with the addition of exogenous variables, the ARIMAX model parameters are obtained.

Table 4. Significance Test Results of ARIMAX Model Parameters

Station	Model	Variables	Coefficient	P-value	Significant
Tanjung priok	(1,0,0)	AR (1)	0.4832	8.225×10^{-5}	Yes
		Humidity	0.1104	2.826×10^{-7}	Yes
		Temperature	-0.0117	0.9318	No
	(0,0,1)	MA (1)	0.4754	0.0008	Yes
		Humidity	0.1126	2.734×10^{-8}	Yes
		Temperature	-0.0136	0.9266	No
	(2,0,2)	AR (1)	1.0957	2.2×10^{-16}	Yes
		AR (2)	-0.7746	3.583×10^{-13}	Yes
		MA (1)	-0.8383	2.2×10^{-16}	Yes
		MA (2)	0.9999	2.2×10^{-16}	Yes
		Humidity	0.0993	2.2×10^{-16}	Yes
		Temperature	-0.1015	2.185×10^{-5}	No

Station	Model	Variables	Coefficient	P-value	Significant
Kemayoran	(1,0,0)			0.1696	
		AR (1)	0.3809	0.0029	Yes
		Humidity	0.1149	5.027×10^{-11}	Yes
		Temperature	-0.0306	0.7985	No
	(0,0,1)	MA (1)	0.3178	0.0037	Yes
		Humidity	0.1164	1.91×10^{-12}	Yes
		Temperature	-0.0582	0.6361	No

Based on parameter significance testing, it can be concluded that the temperature parameter in all models is not significant. However, the temperature variable is still used so that information is not lost.

Jarque-Bera and Ljung-Box Diagnostic Test of ARIMAX Model

Table 5. Diagnostic Test of ARIMAX Model

Tanjung Priok Station			Kemayoran Station		
Model	**P-value Jarque-Bera Test**	**P-value Ljung-Box Test**	**Model**	**P-value Jarque-Bera Test**	**P-value Ljung-Box Test**
(1,0,0)	0.4235	0.8418	(1,0,0)	0.0989	0.9208
(0,0,1)	0.3643	0.9658	(0,0,1)	0.1384	0.6471
(2,0,2)	0.6274	0.5069			

Based on the results of the Jarque-Bera test and the Ljung-Box Test, the P-value > 0.05, indicates that the residuals of the model are normally distributed and there is no autocorrelation.

Forecasting using Ensemble Averaging Method on ARIMA and ARIMAX Models

The modeling results provide rainfall forecasts in Jakarta for the testing period January to June 2023. Forecasting ensemble averaging at Tanjung Priok Station combines forecasting results from several ARIMA and ARIMAX models. The following is a table of forecasting results.

Table 6. Forecasting Rainfall Data in 2023 at Tanjung Priok Station using ARIMA, ARIMAX, and Ensemble Averaging Models

Tanjung Priok Station											
Month	**Actual Data**	**ARIMA (1,0,0)**	**ARIMA (0,0,1)**	**ARIMA (0,0,2)**	**ARIMA (2,0,2)**	**ARIMA (3,0,2)**	**ARIMA ensemble averaging**	**ARIMAX (1 ,0,0)**	**ARIMAX (0,0,1)**	**ARIMAX (2,0,2)**	**ARIMAX ensemble averaging**
January	268.2	110.22	134.23	64.56	115.61	143.93	113.71	137.15	170.07	81.91	129.71
February	496.1	102.54	94.22	86.51	100.70	142.40	105.27	274.08	335.38	204.48	271.31
March	246.7	97.44	94.22	91.71	87.93	123.71	99.00	342.53	384.90	386.97	371.47
April	76.9	93.99	94.22	91.71	79.69	99.17	91.76	110.67	118.38	173.55	134.20
May	117.7	91.65	94.22	91.71	76.57	78.06	86.44	92.81	96.58	135.53	108.31
June	90.6	90.04	94.22	91.71	78.22	64.66	83.77	128.10	132.51	134.01	131.54

Table 6 shows that at Tanjung Priok Station, the ARIMAX (0,0,1) model is close to the actual values in January (179.07) and February (335.38), but the ensemble averaging results of the two models are not better than the smallest ARIMA and ARIMAX models.

Table 7. Forecasting Rainfall Data Year 2023 at Kemayoran Station using ARIMA, ARIMAX, and Ensemble Averaging Models

Kemayoran Station											
Month	**Actual Data**	**ARIMA (1,0,0)**	**ARIMA (0,0,1)**	**ARIMA (0,0,2)**	**ARIMA (0,0,3)**	**ARIMA (0,0,4)**	**ARIMA (2,0,2)**	**ARIMA ensemble averaging**	**ARIMAX (1,0,0)**	**ARIMAX (0,0,1)**	**ARIMAX ensemble averaging**
January	170.9	123.51	116.17	91.45	89.89	147.79	147.27	119.35	101.09	106.70	103.89
February	561.3	115.28	103.59	105.82	77.51	77.97	126.36	101,09	369.68	420.33	395.01
March	236.0	109.98	103.59	102.38	93.59	62.32	104.27	96,02	297.38	321.90	309.63
April	167.5	106.52	103.59	102.38	99.47	81.30	87.29	96,76	97.66	96.64	97.14
May	106.2	104.25	103.59	102.38	99.47	95.51	77.84	97,17	109.56	105.83	107.69
June	127.2	102.73	103.59	102.38	99.47	95.51	76.06	96,62	121.95	120.11	121.03

While in Table 7, it shows that at Kemayoran Station the ARIMAX (0,0,1) model is closest to the actual value seen in February (420.33) and March (321.90) but the ensemble averaging results of the two models are not better than the smallest ARIMA and ARIMAX models.

Model Accuracy Using Symmetric Mean Absolute Percentage Error (SMAPE)

From the testing data, the SMAPE values of the ARIMA, ARIMAX, and ensemble averaging models are presented in the table below.

Table 8. SMAPE Value

Tanjung Priok Station		Kemayoran Station	
Model	**SMAPE**	**Model**	**SMAPE**
ARIMA (1,0,0)	57.87 %	ARIMA (1,0,0)	50.75 %
ARIMA (0,0,1)	56.42 %	ARIMA (0,0,1)	53.98 %
ARIMA (0,0,2)	66.37 %	ARIMA (0,0,2)	58.27 %
ARIMA (2,0,2)	61.25 %	ARIMA (0,0,3)	63.67 %
ARIMA (3,0,2)	56.12 %	ARIMA (0,0,4)	65.08 %
ARIMA ensemble averaging	58.73 %	ARIMA (2,0,2)	60.48 %
ARIMAX (1,0,0)	41.47 %	ARIMA ensemble averaging	58.09 %
ARIMAX (0,0,1)	37.83 %	ARIMAX (1,0,0)	29.25 %
ARIMAX (2,0,2)	60.64 %	ARIMAX (0,0,1)	27.59 %
ARIMAX ensemble averaging	44.67 %	ARIMAX ensemble averaging	28.35 %

At Tanjung Priok Station, the ARIMAX (0,0,1) model obtained the lowest SMAPE of 37.83%, while at Kemayoran Station, the lowest SMAPE value was in the ARIMAX (0,0,1) model with 27.59%. Even so, the level of forecasting accuracy at Kemayoran Station is better than at Tanjung Priok. The SMAPE of ARIMA ensemble averaging in both is in the middle of the SMAPE values of the ARIMA models that make it up, as well as the ARIMAX ensemble averaging model. Thus, the method that will be the best solution for future forecasting is ARIMAX.

CONCLUSION

From the research results, in modeling rainfall in Jakarta, the significant exogenous variable for ARIMAX modeling is humidity. In addition, the ensemble averaging method produces accuracy values that are not better than the best ARIMA or ARIMAX models.

This shows that the ensemble averaging method does not improve the accuracy of either the ARIMA or ARIMAX models. However, the ensemble averaging method may be able to overcome the problem of incorrect selection of the best model in the commonly used ARIMA or ARIMAX modeling. In this case, it is obtained that the level of forecasting accuracy of the ARIMAX (0,0,1) model at Kemayoran Station with a SMAPE value of 27.59% is better than at Tanjung Priok with a SMAPE value of 37.83%.

In this study, there has been no observation on whether there is an effect of the number of ensemble averaging models used in improving the accuracy of the ensemble averaging model (Rahayu et al., 2022). As a follow-up step, this requires further research to determine the number of forming models in order to obtain an ensemble averaging model with the best accuracy in ARIMA and ARIMAX models.

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