FORECASTING BANK INDONESIA CURRENCY INFLOWS

KPW TASIKMALAYA JAWA BARAT WITH CLASSICAL AND MODERN METHOD

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**ABSTRACT**

The availability of currency at Bank Indonesia (BI) can be reviewed by means of an outflow of currency known as inflow. The amount of money circulating in society will affect the economic condition of a country, so that Bank Indonesia (BI) prepares a plan for the need for rupiah currency. This study aims to predict the currency inflow in Tasikmalaya Bank Indonesia (BI) KPw using ARIMA modeling, ARIMAX, Decomposition Method, Winter's Method, MLP (Multilayer Perceptron) or FFNN (Feed Forward Neural Network), Time Series Regression, Naïve Method and Hybrid Model. Of the eight time series methods, both classical and modern, we will look for which method gives the best forecast accuracy results with the criteria of RMSE, MAPE and MAD. The resulting conclusion is Hybrid ARIMA-NN, which is a combination of the ARIMA model with the neural network, does not guarantee better forecasting performance. As mentioned in the results of M3 Competition, the more complex the method used does not mean the method will produce better accuracy than the simple (classical) method. In this West Java Tasikmalaya BI KPw inflow data forecast, the conclusion is that the time series regression method has the smallest modeling criteria value compared to other methods.

Keywords : *Hybrid ARIMA-NN, Time Series Regression, Inflow, Outflow, Bank Indonesia*

1. Introduction

Bank Indonesia is an independent state institution and is the central bank of the Republic of Indonesia which has a single objective, namely to achieve and maintain the stability of the rupiah value. In carrying out its duties, Bank Indonesia prepares a money requirement plan (RKU). Currency is a cash payment instrument that has an important function in supporting economic transactions. This is because almost all economic activities, both production, consumption and investment, always involve money. The currency circulated by Bank Indonesia is used as a legal tender in the territory of the Republic of Indonesia.

The circulation of currency both in the public and in the banking system is regulated by Bank Indonesia. The availability of currency fit for circulation (ULE) can be reviewed through the outflow of currency in Bank Indonesia [1]. The flow of money out of Bank Indonesia to banks and the public is known as an outflow, while the flow of money from banks and the public to Bank Indonesia is referred to as an inflow. The development pattern of the Eligible Currency (ULE) is inseparable from the development of national economic activity and seasonal patterns, where the increase in ULE occurs in the period leading up to religious holidays, holidays and school enrollments and the new year.

Several forecasting methods are used to model time series data. However, the use of this forecasting method must be adapted to the conditions or data patterns so that the best model can be obtained [2]. In this study, the aim of this research is to predict the currency inflow in Tasikmalaya Bank Indonesia (BI) KPw using ARIMA modeling, ARIMAX, Decomposition Method, Winter's Method, MLP (Multilayer Perceptron) or FFNN (Feed Forward Neural Network), Time Series Regression, Naïve Method. and Hybrid Models. Of the eight time series methods, both classical and modern, we will look for which method gives the best forecast accuracy results with the criteria of RMSE, MAPE and MAD.

Until now, Bank Indonesia did not yet have a standard method for predicting the value of currency inflow in a KPw [3]. Thus, the results of this study are expected to become one of the main policies or inputs for Bank Indonesia in forecasting currency inflow in a KPw. Based on the information related to the forecasting of currency inflows, it is also hoped that it will assist BI in implementing rupiah currency management policies which include planning, printing, spending, circulating, withdrawing and destroying rupiah currency.

1. Literature Review
	1. ARIMA and ARIMAX Model

Seasonal ARIMA model has p order as operator of AR, order d is differencing, order q is operator of MA. In the ARIMA model (p, d, q), the future value of a variable is assumed to be a linear function of several past observations and random error. ARIMA model (p, d, q) in general, namely.

 $ϕ\_{p}\left(B\right)\left(1-B\right)^{d}Z\_{t}=θ\_{0}+θ\_{q}\left(B\right)a\_{t}$ (1)

with $ϕ\_{p}\left(B\right)=\left(1-ϕ\_{1}B-…-ϕ\_{p}B^{p}\right),θ\_{q}\left(B\right)=(1-θ\_{1}B-…-θ\_{q}B^{q})$

is the intercept in the model for the d difference. ARIMA modeling can be done using three procedures, namely model identification, model estimation and diagnostic check. Model identification is a methodology to identify the need for a transformation such as a transformation for stationary in variance, differencing transformations, the decision to enter the parameter θ0 when d> 0 and the determination of the order p and q in ARIMA. Estimation of the parameters used in this study used conditional least squares then continued with statistical tests to determine whether these parameters were significant or not.

 Time series modeling by adding several variables that are considered to have a significant effect on data is often done to increase the accuracy of forecasting carried out in a study [4]. The ARIMAX model is a modification of the seasonal ARIMA base model with the addition of a predictor variable. The variation calendar effect is one of the predictor variables that is often used in the modeling. In general, if Yt is a time series with a variation calendar effect, the ARIMAX model is written as follows:

$Y\_{t}=β\_{1}V\_{1,t}+β\_{2}V\_{2,t}+…+β\_{p}V\_{p,t}+\frac{θ\_{q}(B)ΘQ(B^{S})}{∅\_{p}(B)ΦP(B^{S})\left(1-B\right)^{d}(1-B^{S})^{D}}a\_{t}$ (2)

The modeling above consists of response variables, namely time series data and calendar variations that act as dummy variables. The steps to complete the analysis using the ARIMAX model are as follows:

1. Determination of dummy variables based on the variation calendar period
2. Perform regression modeling with equations:

$$Y\_{t}=β\_{1}V\_{1,t}+β\_{2}V\_{2,t}+…+β\_{p}V\_{p,t}+w\_{t}$$

1. Modeling the residuals from the regression analysis using the ARIMA model
2. Perform overall modeling for ARIMAX
3. Checking the significance of parameters and diagnostic tests so that the stationary process and the error of the model reach a white noise condition.
	1. Decomposition and Winter's Method

Decomposition is a time series data analysis approach to identify component factors that affect each value of the data. Each component is identified separately. The projections of each component can then be combined to produce a forecast of the future value from the time series data [5]. Several decompositions have been developed and used:

1. Additive Decomposition

Additive Decomposition decomposes time series data on the components of trend, seasonality, cycle and error. This method identifies future forecasts and adds up the projected results of the forecasts. The model is assumed to be additive (all components are added to get the forecast result). The equation of this model is:

 $X\_{t}=T\_{t}+C\_{t}+S\_{t}+I\_{t}$ (3)

Xt is time series data, Tt is a trend component, Ct is a cycle component, St is a seasonal component, and It is an irregular component [6].

1. Multiplicative Decomposition

Multiplicative decomposition decomposes time series data on the components of trend, seasonality, cycle and error and then predicts future values. The model is assumed to be multiplicative (all components are multiplied by one another to get the forecast model).

Winter's linear exponential smoothing method is used for forecasting if the data has a seasonal component. The Winter's method is based on three smoothing equations, namely the overall smoothing equation, trend smoothing, and seasonal smoothing equations. The three equations of Winter's exponential smoothing are as follows.

 $S\_{t}=a\left(X\_{t}-I\_{mt-L}\right)+\left(1-α\right)\left(S\_{t-1}+b\_{t-1}\right)$ (4)

The Winter's method requires three smoothing parameters (alpha, beta, and gamma) which can be values between 0 and 1, so many combinations must be tried before the optimal value of the three parameters is determined. An alternative method that can reduce doubts about the optimal value is to find a better initial value estimate, then assign a small value to the three smoothing parameters (about 0.1 to 0.3). A value of 0.1 makes the forecast too cautious, while a value of 0.3 gives a more responsive system.

* 1. MLP (Multilayer Perceptron) or FFNN (Feed Forward Neural Network) and Time Series Regression

Artificial Neural networks or neural networks are information processing systems that have similar characteristics to human neural networks. There are 3 types of biological components that build artificial neural networks, namely dendrites, soma and axons. The architecture used in this study is the Multi Layer Perceptron (MLP). Multi Layer Feed Forward Neural networks (FFNN) or Multi Layer Perceptron (MLP) are perceptrons with the addition of one or more hidden layers placed between the input and output networks. MLP output value (Zt) with one hidden layer is calculated through the equation below.

 $\hat{Z}\_{t}=φ\_{k}(b\_{k}+\sum\_{j\rightarrow k}^{}w\_{kj}a\_{j}(b\_{j}+\sum\_{i\rightarrow j}^{}w\_{ji}z\_{t-i}))$ (5)

Regression in the context of time series has the same form as general linear regression [7]. By assuming a dependent output or form yt, for t = 1,2,…,n, which is influenced by the possibility of input data or independent, where the input is fixed and known, this relationship can be shown by a linear regression model [8]. If yt data has trend, trend (t) used as input, which can be written as follows:

 $y\_{t}=β\_{0}+β\_{1}S\_{1,t}+β\_{2}S\_{2,t}+…+β\_{s}S\_{s,t}+a\_{t}$ (6)

where wt as residual, which undergoes an independent and identical process and is normally distributed with a mean value of 0 and variance $σ\_{w}^{2}$. The form of seasonal data S1,t, S2,t, …., Ss,t is a dummy variable for the seasonal form. For example, if the data is monthly, then there are 12 seasonal dummy variables, 1 dummy for 1 month. If the data is quarterly, then there are 3 dummy variables, 1 dummy for the first quarter and so on.

* 1. Naïve Method and Hybrid Model

The naïve model is the simplest method of forecasting. In time series data, using a naïve approach will produce an estimate equal to the last observed value [9]. If the time series is believed to have seasonality, a naive seasonal approach may be more appropriate where the estimate equals the values from last season. The naïve method can also use drift, which takes the last observation plus the average change from the first to the last observation. The naïve model for each condition is presented as follows:

For stationary data :

 $\hat{Y}\_{t+1}=Y\_{t}$ (7)

For trend data :

 $\hat{Y}\_{t+1}=Y\_{t}+(Y\_{t}-Y\_{t-1})$ (8)

For seasonal data

 $\hat{Y}\_{t+1}=Y\_{(t+1)-s}$ (9)

Hybrid is a combination of two or more systems in one function, in this case it is a combination of ARIMA and Neural Network. Many researchers use the hybrid method because it is hoped that it can complement each other because in the real world it is rare to find time series events that are purely linear or purely non-linear. [10]. In general, the combination of linear and non-linear time series models can be written as follows :

 $y\_{t}= L\_{t} + E\_{t} $ (10)

where Lt denotes the linear components and Et mdenotes a non-linear component. There are two components that must be estimated from the data, namely, for example, the ARIMA model is used to solve linear cases, where the residuals of the linear model still contain non-linear relationship information. Can be written :

 $e\_{t} = y\_{t}-\hat{L}\_{t}$ (11)

where ARIMA forecast value at time t. The equation of the residuals for the NN model can be written as follows:

 $e\_{t}=f\left(e\_{t-1}∙e\_{t-2}… e\_{t-n}\right)+ε\_{t}$ (12)

where f is a non-linear function described by NN and εt is random error, so the combination function to predict is  =  + .

* 1. Best Model Selection

The best model is selected if there is more than one suitable model. In the out-sample approach, the best model will be selected based on the smallest forecast error value [11]. The criteria used in this study are RMSE, MAPE and MAD which are formulated as follows.

RMSE (Root Mean Square Error)

 $RMSE=\sqrt{\frac{\sum\_{}^{}(Y\_{t}-Y\_{t+1})^{2}}{n}}$ (13)

MAPE (Mean Absolute Percentage Error), measures the accuracy of the model's estimated value, expressed in terms of the mean absolute percentage of errors:

 $MAPE=\frac{\sum\_{}^{}|(y\_{t}-\hat{y}\_{t})/y\_{t}|}{n}×100$ (14)

MAD (Mean Absolute Deviation), measures the accuracy of the estimated value of the model, expressed in terms of the absolute mean error:

 $MAD=\frac{\sum\_{}^{}|(y\_{t}-\hat{y}\_{t})|}{n}$ (15)

1. Research methodology

The data used is secondary data consisting of currency inflow data in the KPw Bank Indonesia (BI) Tasikmalaya, West Java. The data period used is monthly data from January 2003 to December 2014. The variable used is the cash inflow data of BI KPw Tasikmalaya West Java. The steps in forecasting currency inflow at KPw BI Tasikmalaya, West Java are dividing the data into two parts, namely the January 2003-February 2013 period used as in-sample data while March 2014-December 2014 is used as out-sample data. for modeling (training), while the out sample data is used for selecting the best forecast (testing).

Then apply ARIMA, ARIMAX, Decomposition Method, Winter's Method, MLP (Multilayer Perceptron) or FFNN (Feed Forward Neural Network), Time Series Regression, Naïve Method and Hybrid Model on currency inflow data at KPw Bank Indonesia (BI), Tasikmalaya Java. West. The next step is to calculate the best model selection with an out-sample approach, the best model will be selected based on the smallest forecast error value. The criteria used are RMSE, MAPE and MAD and draw conclusions.

1. Analysis and Discussion
	1. ARIMA and ARIMAX Model

The first stage in time series analysis is to identify the time series plot used to view the currency inflow at Bank Indonesia (BI) KPw Tasikmalaya, West Java.



Picture : Timeseries Plot and Plot ACF Inflow KPw BI Tasikmalaya

Based on the picture 1, it can be seen that the data on currency inflow in the KPw Bank Indonesia (BI) Tasikmalaya, West Java is not stationary. The data is not stationary in the mean because it has an uptrend and shows a slow downward ACF pattern, so it is necessary to handle differencing and transformations.



Picture : Timeseries Plot, ACF and PACF Inflow After Differencing and Transformation

Based on the ACF and PACF plots in Figure 2 It can be seen that the seasonal pattern disappears after differencing 1.The seasonal pattern that is formed at the beginning is no longer visible after differencing 1, so the predictive model formed after differencing is ARIMA (0,1,1)(0,1,1)12 and ARIMA (1,1,1)(1,1,1)12. The next step after identifying the ARIMA model is estimating parameters and testing the significance of the parameters. The method used in parameter estimation is Conditionally Least Square (CLS). The parameter estimates for each ARIMA model provide the results in the Table 1.

Table : Estimation and Testing of the Significance of Parameters in the ARIMA Model

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Estimated Model** | **Parameter** | **Estimate** | **t-value** | **P-value** | **Decision** |
| ARIMA (0,1,1)(0,1,1)12 | MA1 | 0.6590 | 9.23  | 0.000 | significant |
| SMA12 | 0.8105 | 10.53  | 0.000 | significant |
| ARIMA (1,1,1)(1,1,1)12 | AR1 | -0.1078 | -0.74  | 0.458 | Not significant |
| SAR12 | 0.1429 | 1.04  | 0.300 | Not significant |
| MA1 | 0.6035 | 5.32  | 0.000 | Significant |
| SMA12 | 0.8192 | 7.34  | 0.000 | significant |

After obtaining a significant predictive model, the residuals are examined. The residual assumptions that must be fulfilled in the ARIMA model are white noise and normally distributed. Examination of white noise assumptions using the Ljung-Box test with a significant level of α of 5% and H0 rejected if $χ^{2}>χ\_{(α,K-p-q)}^{2}$. The Ljung-Box test results for each ARIMA model show that all models have met the white noise assumption. Furthermore, the residual assumption is tested with normal distribution. The residual assumption test is normally distributed using the Kolmogorov-Smirnov test. The results show that the ARIMA model (0,1,1)(0,1,1)1 dan ARIMA (1,1,1)(1,1,1)12 has fulfilled the normal distribution assumption. Furthermore, the selection of the best model is carried out after a significant model is obtained and meets the assumptions. Selection of the best model is done by looking at the out-sample criteria. The results are summarized in Table 2.

Table : ARIMA and ARIMAX Best Model Selection

|  |  |  |  |
| --- | --- | --- | --- |
| **Estimated Model** | **RMSE Value** | **MAD Value** | **Nilai MAPE Value** |
| ARIMA (0,1,1)(0,1,1)12 | **164641.6** | **137882.1** | **17.960** |
| ARIMA (1,1,1)(1,1,1)12 | 166985.1 | 139105.1 | 18.354 |
| ARIMAX (0,1,12)  | 238276 | 165342 | 24.56 |
| ARIMAX (0,1,1)  | **138147** | **109870** | **17.89** |

From Table 2 above obtained the best model, namely ARIMA (0,1,1)(0,1,1)12 because it has the smallest out-sample criteria value. The model that is formed is as follows.

Zt = 0.6590 Zt-1 + 0.8105 Zt-2 + Zt-12 - 0.6590 Zt-13 - 0.8105 Zt-14 + at – 1.4695 at-12

Time series modeling by adding several variables which are considered to have a significant influence on the data is often done to increase forecast accuracy. The ARIMAX model is a modification of the seasonal ARIMA base model with the addition of a predictor variable. The variation calendar effect is one of the predictor variables that is often used in modeling [12]. In general, if Yt is a time series with a variation calendar effect, the ARIMAX model shows the best model, namely the ARIMAX Model (0,1,1) with dummy variables. C1t to C4tm1 (Idul Fitri) because it has the smallest out-sample criteria value with a MAPE value of 17.89, an RMSE value of 138147 and an MAD value of 109870.

* 1. Decomposition Method and Winter's Method

The additive decomposition method is assumed to be additive (all components are added to obtain the forecast). The equation of this model is:. Meanwhile, multiplicative decomposition is assumed to be multiplicative (all components are multiplied by one another to obtain a forecasting model). The equation of this model is . The results are summarized in Table 3.

Table : Selection of the Best Model Decomposition Method

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Type** | **Model Component** | **RMSE Value** | **MAD Value** | **MAPE Value** |
| *Multiplicative* | *Trend Plus Seasonal* | 390279 | 314530 | 44.724 |
| *Seasonal Only* | 303325 | 212317 | 27.97 |
| *Additive* | *Trend Plus Seasonal* | 383374 | 307712 | 43.685 |
| *Seasonal Only* | **303371** | **206698** | **26.76** |

From the Table 3 above, the best model is obtained, namely the Additive Seasonal Only Model because it has the smallest out-sample riteria value with a MAPE value of 26.76, an RMSE value of 303371 and an MAD value of 206698.

The Winter's method requires three smoothing parameters (alpha, beta, and gamma) which can be values between 0 and 1, so many combinations must be tried before the optimal value of the three parameters is determined. An alternative method that can reduce doubts about the optimal value is to find a better initial value estimate, then assign a small value to the three smoothing parameters (about 0.1 to 0.3). A value of 0.1 makes the forecast too cautious, while a value of 0.3 provides a more responsive system. The results are summarized in Table 4.

Table : Selection of the Best Model Winter's Method

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Method** | **Alfa** | **Gamma** | **Delta** | **RMSE Value** | **MAD Value** | **MAPE Value** |
| Multiplicative | 0.1 | 0.1 | 0.1 | 403825 | 330218 | 59.836 |
| 0.2 | 0.2 | 0.2 | 413424 | 330235 | 60.097 |
| 0.3 | 0.3 | 0.3 | 844676 | 655915 | 123.904 |
| 0.1 | 0.2 | 0.3 | 416421 | 326800 | 60.093 |
| Additive | 0.1 | 0.1 | 0.1 | 346627 | 291968 | 53.093 |
| 0.2 | 0.2 | 0.2 | 322298 | 269167 | 48.5133 |
| 0.3 | 0.3 | 0.3 | 403406 | 337254 | 63.3611 |
| **0.1** | **0.2** | **0.3** | **317356** | **261791** | **47.340** |
| 0.3 | 0.1 | 0.2 | 330614 | 276957 | 50.195 |
| 0.2 | 0.3 | 0.1 | 320929 | 268634 | 48.007 |

From the Table 4 Above obtained the best model, namely the Additive Model with alpha 0.1, gamma 0.2 and delta 0.3 because it has the smallest out-sample criteria value with a MAPE value of 47.34, an RMSE value of 317356 and an MAD value of 261791.

* 1. MLP (Multilayer Perceptron) or FFNN (Feed Forward Neural Network) and Time Series Regression

MLP modeling is preceded by determining the initial weight for modeling. The initial weight is determined randomly. A training function that updates the weight and bias values developed according to the Levenberg Optimization. Hidden layer nodes are determined by trial and error (1 to 10). The architecture used is Multi Layer Perceptron, with the Backpropagation training algorithm. Inflow data is used as output, and dummy from calendar variations as input in this analysis. The best architecture will be selected with the smallest RMSE. The RMSE results in each hidden layer with a test of 12 are presented in Table 5.

Table : Best Model Selection MLP (Multilayer Perceptron) and Time Series Regression

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **RMSE Value** | **MAD Value** | **MAPE Value** |
| Hidden 1 | 235665 | 175549 | 27.15 |
| Hidden 4 | 295378 | 199753 | 25.83 |
| Hidden 6 | **268281** | **167433** | **20.93** |
| **Lag1** | **129552** | **83671.8** | **10.4170** |
| Lag2 | 289641 | 186613.0 | 24.8509 |
| Lag3 | 276929 | 177611.0 | 22.9769 |

From the Table 5 Above obtained the best model, namely the Hidden Model 6 because it has the smallest out-sample criteria value with a MAPE value of 20.93, an RMSE value of 268281 and an MAD value of 167433. Regression in the context of time series has the same form as general linear regression. Assuming the output or dependent form yt, for t = 1,2,…, n, which is influenced by the possibility of the input or independent data, where the input is fixed and known. The best model is the lag1 time series regression because it has the smallest out-sample criteria value with a MAPE value of 10.417, an RMSE value of 129552 and an MAD value of 83671.8.

* 1. Naïve Method and Hybrid Model

The naïve model is the simplest method of forecasting. In time series data, using a naïve approach will produce an estimate equal to the last observed value. If the time series is believed to have seasonality, a naive seasonal approach may be more appropriate where the estimate equals the values from last season. The results are summarized in Table 6.

Table : Selection of the Best Model Naïve Method

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **RMSE Value** | **MAD Value** | **MAPE Value** |
| Stasioner | 344929 | 221226.5 | 32.407 |
| Trend | 607549 | 420007.3 | 66.939 |
| Seasonal | **159727** | **135304.3** | **21.760** |
| Hidden 4 (Lag2) | 238155 | 167168 | 24.06 |
| Hidden 5 (Lag12) | **215862** | **159553** | **22.51** |

From the Table 6 above, the best model is obtained, namely the naïve seasonal model because it has the smallest out-sample criterion value with a MAPE value of 21,760, an RMSE value of 159727 and an MAD value of 135304.3. Based on the ARIMA analysis, the best model used in forecasting BI KPw Tasikmalaya cash inflow in West Java is obtained, namely the ARIMA (0,1,1)(0,1,1)12 can be written as follows:

**Zt = 0.6590 Zt-1 + 0.8105 Zt-2 + Zt-12 - 0.6590 Zt-13 - 0.8105 Zt-14 + at – 1.4695 at-12**

Then look at the lag cut off in the PACF plot from the residuals obtained from the ARIMA model (0,1,1)(0,1,1)12. Based on the PACF plot, it can be seen that the lag cut off is on the 2nd and 12th lags. Therefore, lag 2 and lag 12 are used as inputs in NN modeling to predict the residuals of the model. ARIMA (0,1,1)(0,1,1)12.

ARIMA model residual forecasting (0,1,1)(0,1,1)12 using NN is done with 2 input lag, which means that there is 1 neuron in the input unit and 4 neurons in the hidden layer, and 12 input lag which means that there is 1 neuron in the input unit and the number of units in the hidden layer is 5 neurons. So that the forecasting results using the ARIMA-NN hybrid for cash inflow data of BI KPw Tasikmalaya West Java shows the best model, namely the ARIMA-NN lag12 hybrid model because it has the smallest out-sample criteria value with a MAPE value of 22.51, RMSE value of 215862 and MAD is 159553.

* 1. Comparison of Best Methods

The following is a comparison of eight methods that have been tried, both classical and modern methods, linear and non-linear methods. The results are summarized in Table 7.

Table : Selection of the Best Time Series Method

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **NO** | **METODE** | **MODEL** | **RMSE Value** | **MAD Value** | **MAPE Value** |
| 1 | ARIMA  | (0,1,1)(0,1,1)12 | 164641 | 137882 | 17.96 |
| 2 | ARIMAX  | (0,1,1) (Idul Fitri) | 138147 | 109870 | 17.89 |
| 3 | Dekomposisi | *Additive Seasonal Only* | 303371 | 206698 | 26.76 |
| *4* | *Winter’s* | Additive alfa 0.1, gamma 0.2 dan delta 0.3 | 317356 | 261791 | 47.34 |
| 5 | MLP (*Multilayer Perceptron*) | Hidden 6 | 268281 | 167433 | 20.93 |
| **6** | **Regresi *Time Series*** | **Lag1** | **129552** | **83671** | **10.41** |
| 7 | Metode Naïve | Seasonal | 159727 | 135304 | 21.76 |
| 8 | Model *Hybrid* | Hidden 5 (Lag12) | 215862 | 159553 | 22.51 |

From the Table 7 above, the best method is obtained, namely the Time Series Regression method because it has the smallest out-sample criteria value with a MAPE value of 10.41, an RMSE value of 129552 and an MAD value of 83671.

1. Conclusion

Hybrid ARIMA-NN, which is a combination of the ARIMA model with the neural network, does not guarantee better forecasting performance. As mentioned in the results of the M3 Competition, the more complex the method used does not necessarily mean that the method will produce better accuracy than the simple (classical) method. In the forecast of the KPw BI Tasikmalaya BI data inflow, the conclusion is that the time series regression method has a criteria value. the smallest modeling compared to other methods.

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