

# Forecasting Inflow and Outflow of Money Currency in East Java Using a Hybrid Exponential Smoothing and Calendar Variation Model

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**Abstract.** Money currency availability in Bank Indonesia can be examined by inflow and outflow of money currency. The objective of this research is to forecast the inflow and outflow of money currency in each Representative Office (RO) of BI in East Java by using a hybrid exponential smoothing based on state space approach and calendar variation model. Hybrid model is expected to generate more accurate forecast. There are two studies that will be discussed in this research. The first studies about hybrid model using simulation data that contain pattern of trends, seasonal and calendar variation. The second studies about the application of a hybrid model for forecasting the inflow and outflow of money currency in each RO of BI in East Java. The first of results indicate that exponential smoothing model can not capture the pattern calendar variation. It results RMSE values 10 times standard deviation of error. The second of results indicate that hybrid model can capture the pattern of trends, seasonal and calendar variation. It results RMSE values approaching the standard deviation of error. In the applied study, the hybrid model give more accurate forecast for five variables : the inflow of money currency in Surabaya, Malang, Jember and outflow of money currency in Surabaya and Kediri. Otherwise, the time series regression model yields better for three variables : outflow of money currency in Malang, Jember and inflow of money currency in Kediri.

## 1. Introduction

Money currency is one of cash payment which has important functions to support economic transactions. The circulation of money currency in the bank and community are regulated by Bank Indonesia regulation No.14 /7/ PBI on June 27, 2012 [1]. Bank Indonesia is an independent state agency and central bank of Republic Indonesia, which has one single purpose to achieve and keep stability of rupiah [2]. Outflow of money currency in East Java on July 2015 is 13.456 trillion, while inflow of money currency in East Java reaches 10.719 trillion [3]. Therefore, it is important to research the inflow and outflow of money currency RO of BI in East Java. The objective of this



research is to forecast the inflow and outflow of money currency in each RO of BI in East Java by using a hybrid exponential smoothing based on state space approach and calendar variation model.

Based on previous research showed that inflow and outflow of money currency contains patterns not only seasonal and trends but also calendar variation. If only use exponential smoothing models, it will give bad result. Therefore, this research will combine or hybrid exponential smoothing model with state space approach and calendar variation model. It hopes the hybrid model is a practical forecasting model and can capture three patterns to generate small forecasting error value. Previous research about hybrid modeling was made by Zhang [4] which showed that comparison method between ARIMA, NN, and hybrid ARIMA-NN the most accurate forecast is a hybrid ARIMA-NN model.

Previous research about netflow of money currency is made by Karomah [5] and Wulansari [6] using ARIMAX which showed that netflow of money currency is affected by Eid-holidays, seasonal effect and consumer price index. Hanim [7] and Masun [8] research about forecasting inflow and outflow of money currency using ARIMAX and regression time series. Their research showed that inflow and outflow of money currency is influenced by Eid-holidays and annual seasonal effects. Previous research about ARIMAX and regression two level model for forecasting sales data on retail company is made by Suhartono, Lee and Prastyo [9] which showed that ARIMAX and regression two level model can capture the effect of calendar variations and produce more accurate forecast. Research about exponential smoothing with state space approach was made by Koehler [10] and Nurhariyadi [11] which showed that exponential smoothing model with handling outlier is better than exponential smoothing model (basic model).

Until now, Bank Indonesia does not have a standard method to predict inflow and outflow of money currency in each RO of BI. This research are expected to be one of the policy for Bank Indonesia to forecast inflow and outflow of money currency in each RO of BI.

## 2. Literature Review

### 2.1. Time Series Regression Model

Time series regression model for data that contain trend pattern is following the equation [12].

$$Y_t = \beta_0 + \beta_1 t + a_t, \quad t=1,2,3,\dots,n \quad (1)$$

with  $a_t$  is a residual component that satisfy white noise assumption. While data which has seasonal pattern  $S_{1,t}, S_{2,t}, \dots, S_{s,t}$ . It can be written as follows

$$Y_t = \beta_1 S_{1,t} + \beta_2 S_{2,t} + \dots + \beta_s S_{s,t} + a_t \quad (2)$$

with  $S_{1,t}, S_{2,t}, \dots, S_{s,t}$  is a dummy variable to explain seasonal pattern. Linear regression model for data with calendar variation pattern follow this equation.

$$Y_t = \beta_1 V_{1,t} + \beta_2 V_{2,t} + \dots + \beta_p V_{p,t} + a_t \quad (3)$$

with  $V_{p,t}$  = dummy variable for calendar variation effects into- $p$ .

### 2.2. Single Exponential Smoothing (N,N Method)

General equation single exponential smoothing can be written:

$$\hat{Y}_{t+1} = \hat{Y}_t + \alpha(Y_t - \hat{Y}_t) \quad (4)$$

Forecasting equation single exponential smoothing can be written:

$$\hat{Y}_{t+h|t} = \hat{Y}_{t+1}, \quad h = 2, 3, \dots \quad (5)$$

with state space model is

$$\ell_t = \hat{Y}_{t+1}$$

$$\widehat{Y}_{t+h|t} = \ell_t$$

$$\ell_t = \alpha Y_t + (1 - \alpha)\ell_{t-1}. \quad (6)$$

So, single exponential smoothing model follow this equation [13].

$$\widehat{Y}_{t+1} = \ell_t = \widehat{Y}_t + \alpha(Y_t - \widehat{Y}_t) \quad (7)$$

$$\widehat{Y}_{t+1} = \alpha Y_t + (1 - \alpha)\widehat{Y}_t. \quad (8)$$

### 2.3. Additive Seasonality Model : ETS (A,A,A)

State space model for ETS (A,A,A) can be written as:

$$\mu_t = \ell_{t-1} + b_{t-1} + s_{t-m}$$

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha a_t$$

$$b_t = b_{t-1} + \beta a_t$$

$$s_t = s_{t-m} + \gamma a_t. \quad (9)$$

The forecast function for ETS (A,A,A) follow this equation [13].

$$\widehat{Y}_{t+h|t} = \ell_t + hb_t + s_{t-m+h_m^+}. \quad (10)$$

### 2.4. Multiplicative Seasonality Model : ETS (M,A,M)

State space model for ETS (M,A,M) can be written as:

$$\mu_t = (\ell_{t-1} + b_{t-1})s_{t-m}$$

$$\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha a_t)$$

$$b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})a_t$$

$$s_t = s_{t-m}(1 + \gamma a_t). \quad (11)$$

The forecast function for ETS (M,A,M) follow this equation [13].

$$\widehat{Y}_{t+h|t} = (\ell_t + hb_t)s_{t-m+h_m^+}. \quad (12)$$

### 2.5. Hybrid Exponential Smoothing with State Space Approach and Calendar Variation Model

Hybrid exponential smoothing and calendar variation model can be written in two models.

#### 2.5.1. The First Model

Level 1. The initial regression model

$$Y_t^1 = \delta t + \beta_1 M_{1,t} + \beta_2 M_{2,t} + \dots + \beta_s M_{s,t} + \sum_g \alpha_g D_{g,t} + \sum_g \gamma_g D_{g,t+1} + u_t \quad (13)$$

Level 2. The regression model with calendar variation effect.

$$\widehat{\alpha}_g^* = a + bg$$

$$\widehat{\gamma}_g^* = c + dg \quad (14)$$

#### 2.5.2. The Second Model.

$$\ell_t = \alpha y_t + (1 - \alpha)\ell_{t-1} \quad (15)$$

$$\widehat{y}_t^* = \ell_t$$

### 2.5.3. The First Forecast

$$\hat{Y}_t = \hat{Y}_t^1 + \hat{\alpha}_g^* + \hat{\gamma}_g^* + \hat{y}_t^* \quad (16)$$

### 2.5.4. The Second Forecast

$$\hat{Y}_t = \hat{Y}_t^1 + \hat{y}_t^* \quad (17)$$

### 2.6. Selection The Best Model

In out-sample approach, the best model will be selected based on the smallest forecasting error value. This research use criteria RMSE (Root Mean Square Error). RMSE is defined as follows [14].

$$RMSE = \sqrt{\frac{1}{L} \sum_{l=1}^L (Y_{n+l} - \hat{Y}_n(l))^2} \quad (18)$$

with

$Y_{n+l}$  : actual value for out-sample data into- $l$  or data at time into- $(n+l)$ ,  $l = 1, 2, \dots, L$

$\hat{Y}_n(l)$  : forecast results of out-sample data into- $l$ .

## 3. Research Methodology

### 3.1. Source of Data

This research use secondary data that consists of inflow and outflow of money currency in East Java from January 2003 into December 2014. It was obtained from Bank Indonesia. The period January 2003-December 2013 is used as in-sample data while January 2014-December 2014 is used as out-sample data. This research also use simulation study. Simulation data is obtained from the following equation:

$$Y_{t,a} = T_t + S_{t,a} + CV_t + \varepsilon_t \quad (19)$$

$$Y_{t,m} = (T_t \times S_{t,m}) + CV_t + \varepsilon_t \quad (20)$$

- Generate data  $\varepsilon \sim N(0, \sigma_\varepsilon^2)$  with  $n=120$ . This research use  $\sigma_\varepsilon = 3$ .
- Generate data  $T_t$  follow this equation

$$T_t = 10 + 2t. \quad (21)$$

- Generate data  $S_{t,a}$  follow this equation

$$S_{t,a} = 20 + 10 \sin \frac{2\pi t}{12}. \quad (22)$$

- Generate data  $S_{t,m}$  that calculated by addition 12 for each year.
- Determine calendar variation effect  $CV_t$  follow this equation

- effect of Eid-holidays

$$\alpha_g = 5 + 10g \quad (23)$$

- effect before Eid-holidays

$$\gamma_g = 100 - 5g. \quad (24)$$

- Obtain simulation data with additive pattern that calculated by the sum of value  $\varepsilon_t$ ,  $T_t$ ,  $S_{t,a}$  and  $CV_t$  so get the equation (19).

Obtain simulation data with multiplicative pattern that calculated by the sum of value  $\varepsilon_t$ ,  $(T_t \times S_{t,m})$  dan  $CV_t$  so get the equation (20).

### 3.2. Research Variables

The variables are used in this research involve:

**Table 1.** Research Variables

Research Variables	KPw			
	Surabaya	Malang	Kediri	Jember
Inflow	$Y_{1,1t}$	$Y_{1,2t}$	$Y_{1,3t}$	$Y_{1,4t}$
Outflow	$Y_{2,1t}$	$Y_{2,2t}$	$Y_{2,3t}$	$Y_{2,4t}$

While dummy variables are used in this research involve:

a. Dummy of trend following

$L_{1,t}$  : The increase in second period, January 2007- December 2010

$L_{2,t}$  : The increase in third period, January 2011-December 2014

$tL_{1,t}$  : Trend and increase in second period

$tL_{2,t}$  : Trend and increase in third period.

b. Dummy of seasonal (month) following

$M_{1,t}, M_{2,t}, \dots, M_{12,t}$  : January, February, ..., December.

c. Dummy of calendar variation effect based on Eid-holidays with effect number of days before Eid-holidays with a period one month after (T+1), one month before (T-1) and the time Eid-holidays is occurred (T). after (T+1), one month before (T-1) and the time Eid-holidays is occurred (T).

$$D_{g,t} = \begin{cases} 1, & T = t \\ 0, & T \neq t \end{cases}$$

which  $g$  indicates the number of days before Eid-holidays that occurred on  $(g + 1)$  and  $T$  indicates the time Eid-holidays is occurred. This research use two level time series regression model The first level is time series regression equation that produced by initial model. Second level is made by using the coefficient parameter equation that produced by first level. Second level will be used to predict or forecast calendar variation effect on every possibility for many different previous day [8].

i. Level 1. The initial regression model.

$$Y_t = \delta t + \beta_1 M_{1,t} + \beta_2 M_{2,t} + \dots + \beta_S M_{S,t} + \sum_g \alpha_g D_{g,t} + \sum_g \gamma_g D_{g,t+1} + u_t \quad (25)$$

ii. Level 2. The regression model with calendar variation effect.

$$\hat{\alpha}_g^* = a + bg \quad (26)$$

$$\hat{\gamma}_g^* = c + dg \quad (27)$$

with  $\hat{\alpha}_g^*$  and  $\hat{\gamma}_g^*$  is coefficient of parameter estimation results in the first level, and  $a, b, c, d$  is constants. Model at second level is performed if the number of days before Eid-holidays has not been found at the first level model. Forecasting of results can be calculated by the sum of forecast value at the regression model level 1 and level 2.

### 3.3. Step Analysis

Step study will be done in this research is as follows:

### 3.3.1. Simulation Study

- a. Dividing the simulation data into two parts, in-sample and out-sample. Then apply exponential smoothing model for in-sample data.
- b. Evaluation weakness of exponential smoothing model.
- c. Combining exponential smoothing and calendar variation model. The step is as follows:
  - Calendar variation model for simulation data using time series regression. This research use two level regression model.
  - The first model is the sum of forecast value on level 1 and level 2.
  - Error that obtained by first model will analyze using exponential smoothing with state space approach model.
  - Combining predictions of both models. It is calculated by the sum of forecast value at the first model and second model.
  - Evaluate the hybrid model.

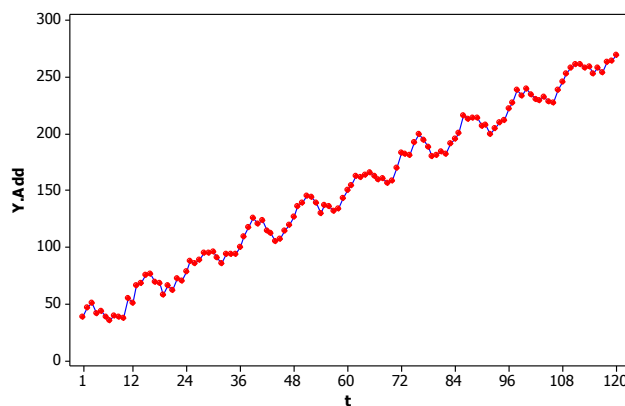
### 3.3.2. Applied Study

- a. Modeling inflow and outflow of money currency in RO of BI Surabaya, in RO of BI Malang, in RO of BI Jember, and in RO of BI Kediri using hybrid model and time series regression model.
- b. Comparing the accuracy of both models to determine the best model.
- c. Forecast inflow and outflow of money currency in East Java by using the best model.

## 4. Analysis And Results

### 4.1. Exponential Smoothing Model on Simulation Data Trend and Seasonal Pattern

The combined graph trend and additive seasonal can be seen in figure 1.



**Figure 1.** Time Series Plot Trend dan Additive Seasona.

Data with trend and additive seasonal patterns produce ETS (A,A,A). State space equation for ETS (A,A,A) can be written as:

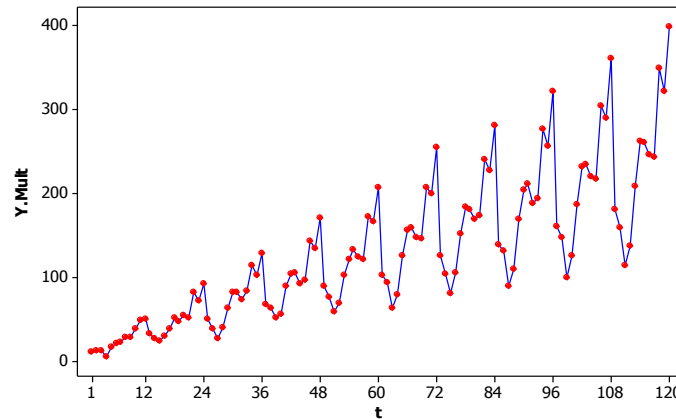
$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + a_t$$

$$\ell_t = \ell_{t-1} + b_{t-1} + 0.0001a_t$$

$$b_t = b_{t-1} + 0.0001a_t$$

$$s_t = s_{t-m} + 0.0001a_t$$

In-sample RMSE value for state space ETS (A,A,A) is 3.42. While out-sample RMSE value for state space ETS (A,A,A) is 3.18. Trend and multiplicative seasonal pattern can be seen in figure 2.



**Figure 2.** Time Series Plot Trend and Multiplicative Seasonal.

Data with trend and multiplicative seasonal pattern produce ETS (M,A,M). State space equation for ETS (M,A,M) can be written as:

$$y_t = (\ell_{t-1} + b_{t-1})s_{t-m} + a_t$$

$$\ell_t = (\ell_{t-1} + b_{t-1})(1 + 0.5565a_t)$$

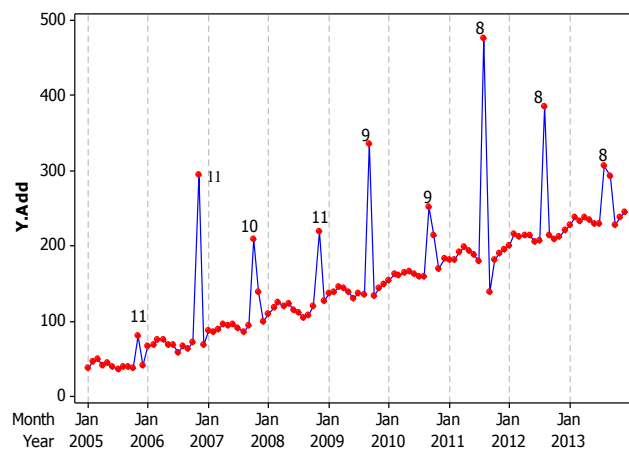
$$b_t = b_{t-1} + 0.0238(\ell_{t-1} + b_{t-1})a_t$$

$$s_t = s_{t-m}(1 + 0.0001a_t)$$

State space model for ETS (M,A,M) produces in-sample RMSE is 4.88. While out-sample RMSE is 3.86. Based on the RMSE value can be obtained information that ETS (M,A,M) and ETS (A,A,A) method is an appropriate model to handle data with trend and seasonal pattern because RMSE value close to the standard deviation of error on simulation data. This is exponential smoothing model for data with trend, seasonal and calendar variation patterns.

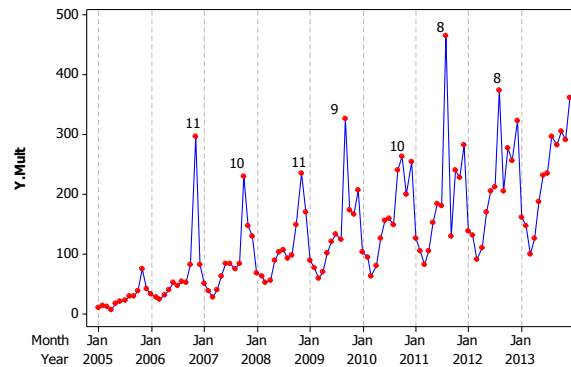
#### 4.2. Exponential Smoothing Model on Simulation Data Trend, Seasonal and Calendar Variation Pattern

The combined graph trend, additive seasonal and calendar variation can be seen in figure 3.



**Figure 3.** Time Series Plot Trend, Seasonal and Calendar Variation (Additive)

While the combined graph trend, multiplicative seasonal and calendar variation can be seen in figure 4.



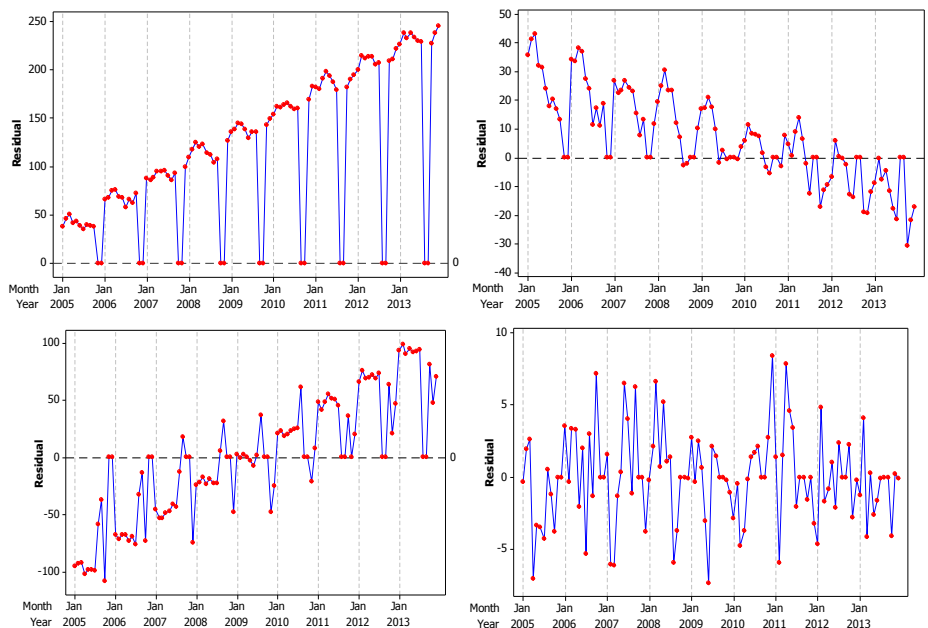
**Figure 4.** Time Series Plot Trend, Seasonal and Calendar Variation (Multiplicative)

When simulation data with trend, additive seasonal and calendar variation pattern were modeled by exponential smoothing method will produce ETS (A,A,A). But the state space model of ETS (A,A,A) produces RMSE value 42.98. Similarly, simulation data with trend, multiplicative seasonal and calendar variation pattern were modeled by exponential smoothing method will produce ETS (M,A,M) with RMSE value 56.82. It was the highest RMSE value.

This condition occurs because the winter's models was designed to handle data with trends and seasonal pattern. In this case, winter's models was not capture calendar variation pattern so RMSE value that produced was not approach standard deviation of the simulated data. Therefore, this research will use a hybrid exponential smoothing with state space approach and calendar variation model to handle this case.

*4.3. Hybrid Model on Simulation Data Trend, Seasonal and Calendar Variation Pattern*

Since there is constraint about calendar variation effect, hybrid model will be written into two equations model. The first model is regression equations with dummy variable calendar variation effect. First model consists of two levels as in equation (20) and (21). While the second model is exponential smoothing equation of residual that produced by the first model. There are the results time series regression (TSR) of the first model for every possibility:



**Figure 5.** Time Series Plot Elimination  $CV_t$  (a),  $T_t + CV_t$  (b),  $S_t + CV_t$  (c),  $T_t + S_t + CV_t$  (d) (Additive Pattern)

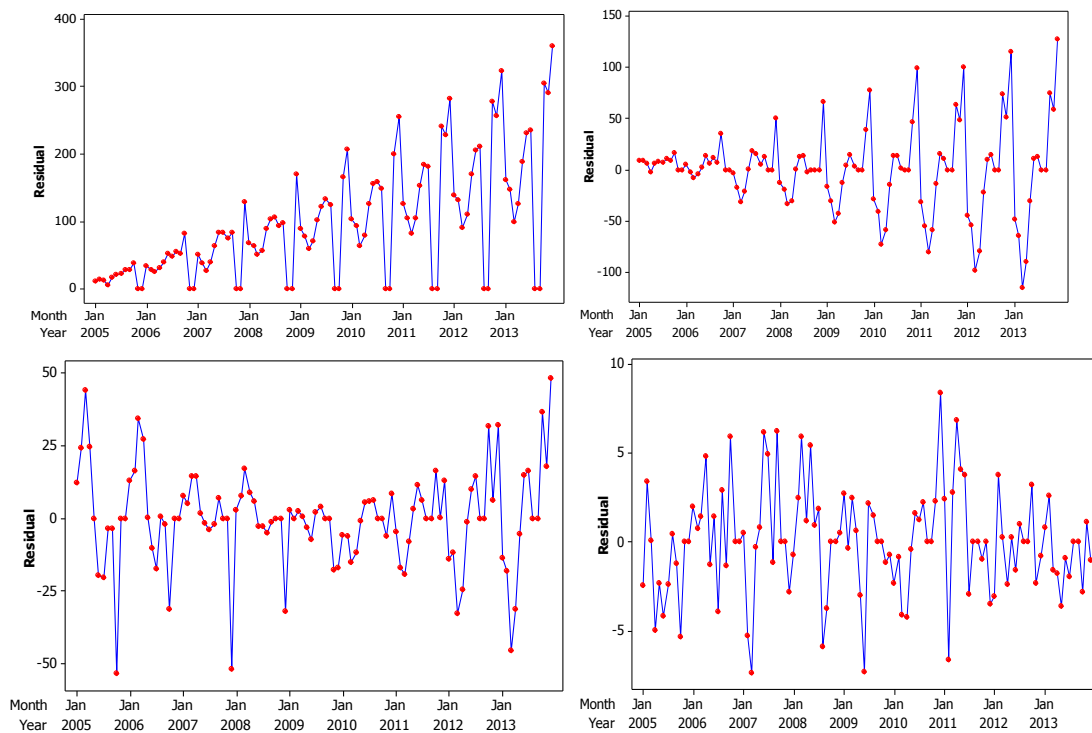


There were a summary of the RMSE value that generated by time series regression model to eliminate calendar variation, trend and seasonal additive effects.

**Table 2** RMSE Value TSR Model on Simulation Data (Additive)

Time Series Regression Model	RMSE
elimination $CV_t$ effect	34.44
elimination $T_t + CV_t$ effect	5.93
elimination $S_t + CV_t$ effect	22.42
elimination $T_t + S_t + CV_t$ effect	<b>3.15</b>

Based on the analysis that has been done, it can be concluded that TSR model for additive data with eliminate calendar variation, trend, and seasonal is appropriate model because it generated RMSE value 3.15. It is close to the standard deviation of error on simulation data. Furthermore, residual that produced by the first model will be modeled by using exponential smoothing model and obtained ETS (A,N,N) model. The results of hybrid time series regression model and ETS (A,N,N) produced in-sample RMSE values 3.15 while for out-sample RMSE value was 3.09. TSR model for multiplicative pattern was as follows.



**Figure 6.** Time Series Plot Elimination  $CV_t$  (a),  $T_t + CV_t$  (b),  $T_t + S_t + CV_t$  (c),  $T_t + S_t + CV_t + T_t S_t$  (d) (Multiplicative Pattern).

There were a summary of the RMSE value that generated by time series regression model to eliminate calendar variation, trend and seasonal multiplicative effects.

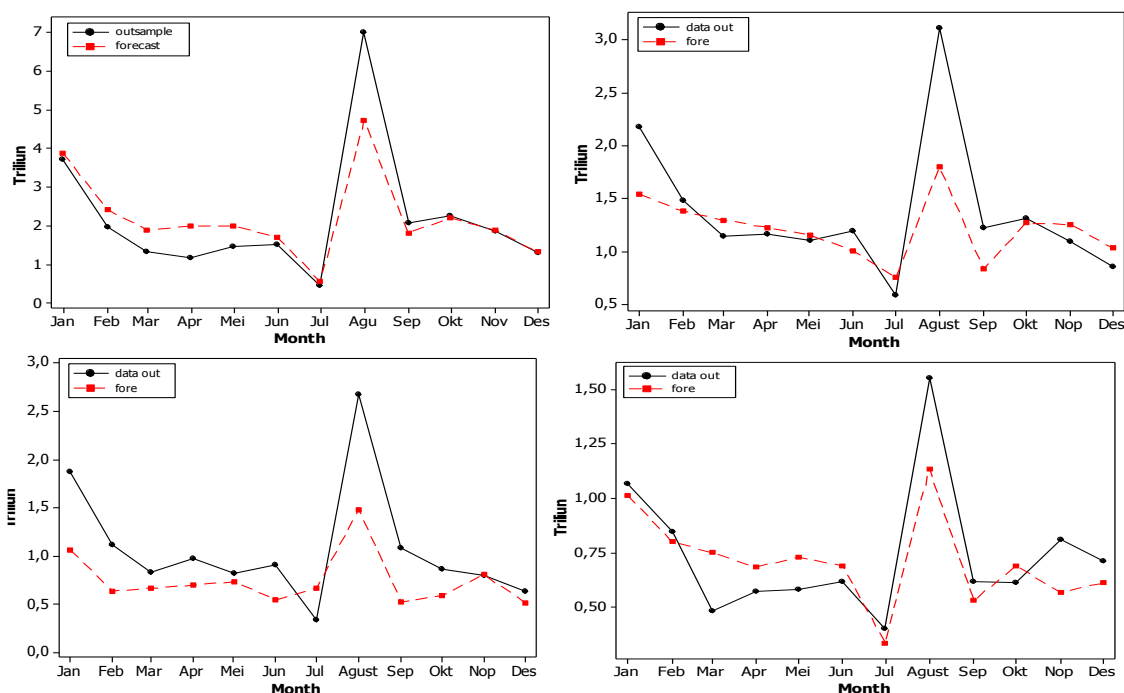
**Table 3** RMSE Value TSR Model on Simulation Data (Multiplicative)

Time Series Regression Model	RMSE
elimination $CV_t$ effect	40.09
elimination $T_t + CV_t$ effect	22.98
elimination $T_t + S_t + CV_t$ effect	16.97
elimination $T_t + S_t + CV_t + T_t S_t$ effect	<b>3.01</b>

Based on the analysis that has been done, it can be concluded that TSR model for multiplicative data with eliminate calendar variation, trend, seasonal and multiplication between trend and seasonal is appropriate model because it generated RMSE value 3.01. It is close to the standard deviation of error on simulation data. Furthermore, residual that produced by the first model will be modeled by using exponential smoothing model and obtained ETS (A,N,N) model. The results of hybrid time series regression model and ETS (A,N,N) produced in-sample RMSE values 3.01 while for out-sample RMSE value was 3.96.

*4.4. Modeling Inflow dan Outflow of Money Currency by Using Hybrid Model*

A hybrid model for inflow and outflow of money currency in East Java produced ETS (A,N,N) when analyzed the second model. Time series plot out-sample data and prediction value for inflow of money currency in East Java can be seen in figure 7.



**Figure 7.** Actual data vs Forecasting inflow 2014 RO of BI Surabaya (a) Malang (b) Kediri (c) Jember (d).

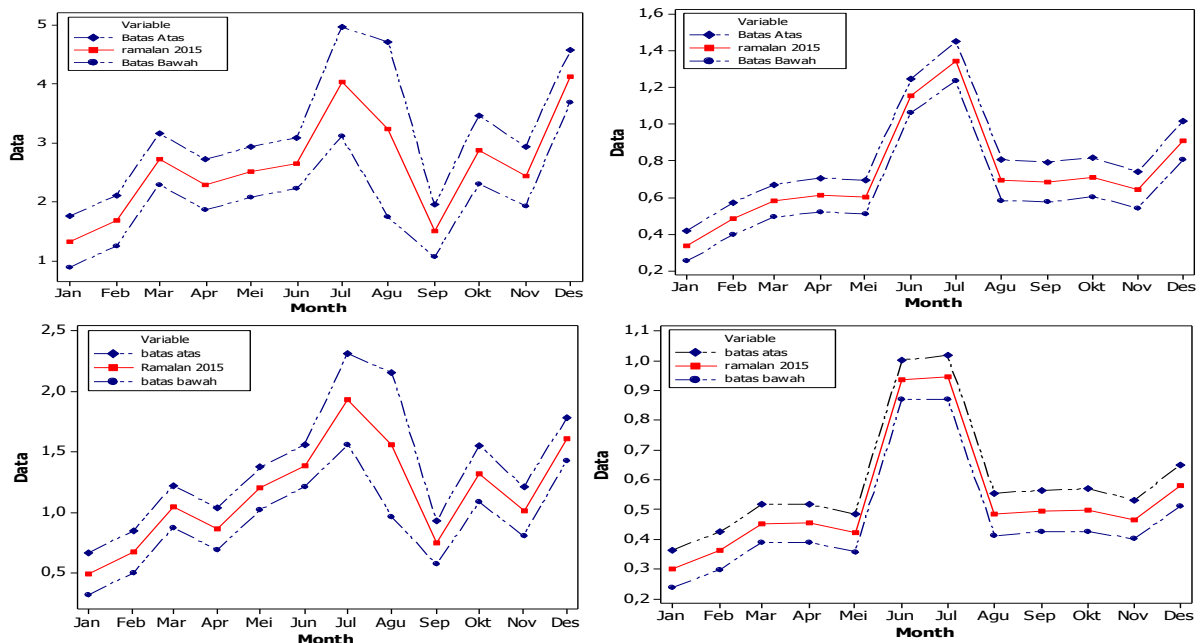
*4.5. Comparison between Hybrid and Time Series Regression Model*

The model has been obtained will be compared using the criteria of goodness models. It can be seen by RMSE value as follows.

**Table 4.** Comparison RMSE Value.

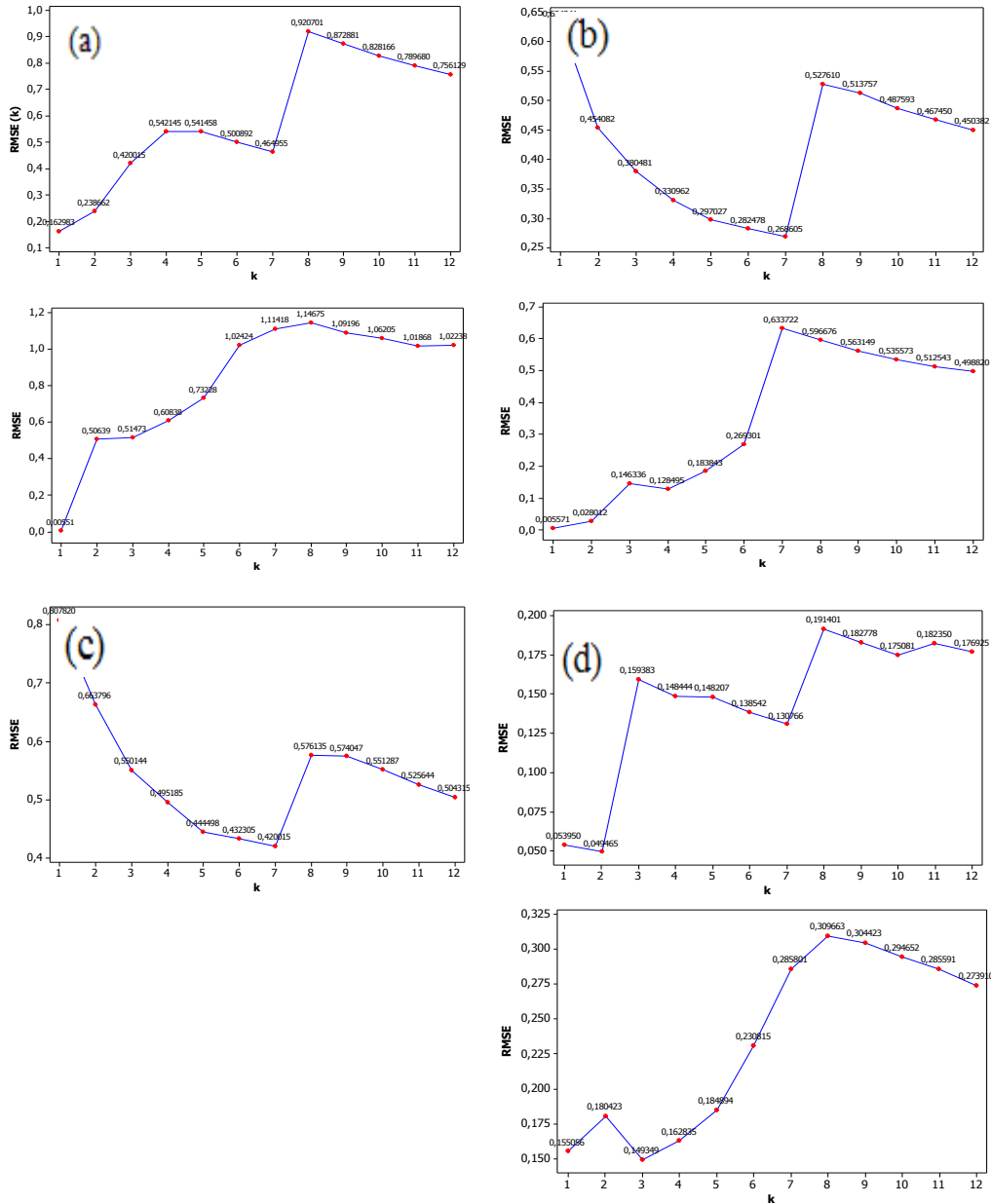
RO of BI		Method	RMSE <i>in-sample</i>	RMSE <i>out-sample</i>
Surabaya	<i>Inflow</i>	Hybrid	0.189	<b>0.787</b>
		Time Series Regression	0.249	1.359
	<i>Outflow</i>	Hybrid	0.204	<b>1.022</b>
		Time Series Regression	0.346	1.189
Malang	<i>Inflow</i>	Hybrid	0.069	<b>0.451</b>
		Time Series Regression	0.082	0.705
	<i>Outflow</i>	Hybrid	0.056	0.529
		Time Series Regression	0.077	<b>0.498</b>
Kediri	<i>Inflow</i>	Hybrid	0.064	0.504
		Time Series Regression	0.085	<b>0.491</b>
	<i>Outflow</i>	Hybrid	0.092	<b>0.433</b>
		Time Series Regression	0.153	0.642
Jember	<i>Inflow</i>	Hybrid	0.028	<b>0.177</b>
		Time Series Regression	0.065	0.284
	<i>Outflow</i>	Hybrid	0.045	0.308
		Time Series Regression	0.063	<b>0.274</b>

Table 4 showed that hybrid model can provide better forecasting results than the time series regression model. Hybrid model for 5 variables while time series regression model for 3 variables. There were time series plot of forecasting inflow and outflow of money currency in 2015 for each RO of BI East Java.



**Figure 8.** Forecasting Inflow and Outflow of Money Currency 2015 (a) RO of BI Surabaya (b) RO of BI Malang (c) RO of BI Kediri (d) RO of BI Jember

There were the results of adaptive RMSE value Inflow and Outflow of moner curenry in East Java by using the best model.



**Figure 9.** Adaptive RMSE Inflow and Outflow of Money Currency (a) RO of BI Surabaya (b) RO of BI Malang (c) RO of BI Kediri (d) RO of BI Jember

Based on figure 9 it can be seen that out-sample RMSE value increases when forecasted 6 or 7 periods. The best model in the case inflow of money currency uses to forecast 7 periods. While in the case outflow of money currency, the best model uses to forecast 6 periods.

**5. Conclusion**

Based on the analysis and results, it can be concluded that hybrid model can provide better forecasting results than time series regression model on simulation study and applied study. Hybrid model for

inflow of money currency in RO of BI Surabaya, Malang, Jember with 3 variables while hybrid model for outflow of money currency in RO of BI Surabaya and Kediri with 2 variables.

In general, a hybrid model for out-sample data produce forecast not optimal because out-sample data consists of surge inflow and outflow of money currency which higher than previous years. To other research, it is suggested by using non-linear model on the second level. So, it can capture the effect of calendar variation better

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