BAREKENG: Jurnal Ilmu Matematika dan Terapan
June 2022 Volume 16 Issue 2 Page 635–642
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol16iss2pp635-642

FORECASTING OF CURRENCY CIRCULATION IN INDONESIA USING HYBRID EXTREME LEARNING MACHINE

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Abstract. *Forecasting currency circulation, including inflow and outflow, is one of Bank Indonesia's strategies to maintain the Rupiah value's stability. The characteristic of inflow and outflow data is that they have seasonal variations. This study proposes a hybrid model by combining decomposition techniques and Extreme Learning Machine to overcome data that has seasonal variations. The forecasting results of the proposed model are compared with the original Extreme Learning Machine. The comparison results show that the forecasting results with the hybrid model have the smallest errors. Thus, the hybrid model can predict data with seasonal variations better than the original Extreme Learning Machine.*

Keywords: *currency circulation, decomposition, extreme learning machine, forecasting, inflow, outflow*.

Article info:

Submitted: 1st March 2022 *Accepted: 6th May 2022*

How to cite this article:
M. D. Kartikasari, "FORECASTING OF CURRENCY CIRCULATION IN INDONESIA USING HYBRID EXTREME LEARNING MACHINE", *BAREKENG: J. Il. Mat. & Ter.*, vol. 16, iss. 2, pp. 635-642, June, 2022.

1. INTRODUCTION

Bank Indonesia (BI) has one objective of achieving and maintaining the stability of the Rupiah value [1]. To achieve this objective, BI, as the central bank, prepares a plan to meet the needs of the Rupiah currency. This planning can be done by forecasting the currency circulation, including inflow and outflow. Inflow is money that enters BI through deposit activities, while outflow is money that comes out of BI through withdrawal activities [2]. In general, fluctuations of inflow and outflow in Indonesia contain seasonal variations. Seasonality is a periodic and recurrent pattern caused by factors such as weather, holidays, repeating promotions, as well as the behavior of economic agents [3–5]. Several forecasting techniques are commonly used to forecast data with seasonality, including Holt Winters' exponential smoothing [6], [7], decomposition [8], [9], and SARIMA model [10]. The decomposition for forecasting seasonal time series is to remove seasonal variations. The decomposition decomposes a seasonal time series into trend-cycle, seasonal, and remainder components. Seasonal effects are forecasted and removed from the data before other components are forecasted.

Recently, the Artificial Neural Network (ANN) model has been widely used for time series forecasting, for example, in agriculture [11], [12], finance and economic [13]–[15], energy [16]–[18], weather [19]–[21], transportation [22], and others. The ANN model can forecast something in the future based on historical patterns in the past [23]. The ANN model has no special assumptions that need to be made in the model and the underlying relationships are determined only through data mining. Many methods in the ANN model have been proposed for forecasting, one of which is Extreme Learning Machine (ELM) introduced by Huang et al. [24]. ELM is a fast-learning algorithm of single-hidden layer feedforward neural networks (SLFNs). Compared with the traditional neural networks, the ELM algoritshm has the advantages of fast learning speed and good generalization.

In this study, forecasting of currency inflow and outflow is proposed using a hybrid model by combining decomposition and ELM techniques. Trend-cycle components of inflow and outflow data in the decomposition technique were analyzed by ELM. The seasonal component is forecasted by the average method. The results of the analysis using the proposed model are then compared with the original ELM.

2. RESEARCH METHODS

Data used in this study are data of currency inflow and outflow in billion rupiah, with observation period January 2003 until June 2020. The data obtained from Bank Indonesia. Data from January 2003 up to and including December 2017 are used as training data, data observed after 2017 are used as testing data.

This research consists of several stages. First, the research begins by describing the data to find out the pattern of the data used. Then, it is continued by dividing the data into training and testing. The training data is decomposed into trend-cycle, seasonal, and remainder components. Furthermore, the training data is analyzed using the hybrid model, by combining decomposition and ELM. From the results of the analysis, it is continued by calculating Mean Absolute Percentage Error (MAPE) for training and testing. The research process ends by comparing the results of the analysis with the hybrid ELM model and the original ELM. Figure 1 shows the stages of research in a flowchart.

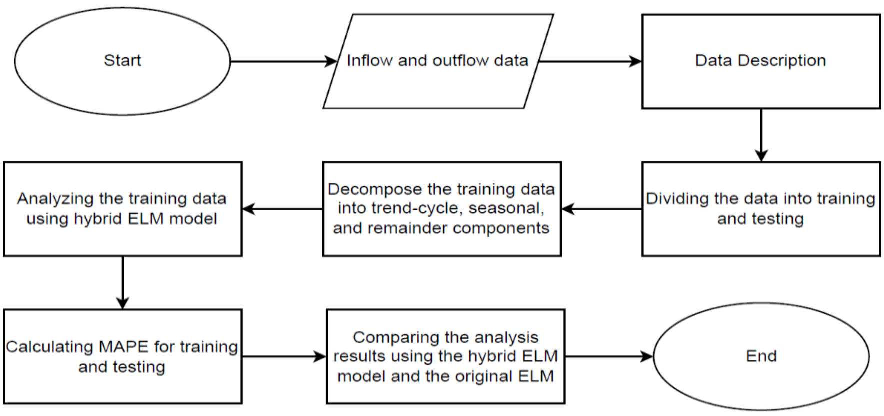

Figure 1. Stages of Research

2.1 Decomposition

Decomposition method originated in the 1920's. The decomposition method can assume an additive or multiplicative model. The additive decomposition is used if seasonal variations, or variations around trends-cycles, are relatively stable and do not depend on the time series level. Meanwhile, the multiplicative decomposition is used if seasonal variations, or variations around trends-cycles, are fluctuate and appear to be proportional to the time series level. Following [25], here are the additive and multiplicative decomposition procedures.

If additive decomposition is assumed, it can be written as

$$X_t = S_t + T_t + R_t, \tag{1}$$

where x_t is the data, S_t is the seasonal component, T_t is the trend-cycle component, and R_t is the remainder component, all at period t. Multiplicative decomposition can be written as

$$X_t = S_t \times T_t \times R_t. \tag{2}$$

The following is the procedure for performing additive decomposition:

Step 1: If m is an even number, apply moving average of order 2 to moving average of order m, $\text{MA}(2 \times m)$, to estimate trend-cycle component $\hat{T}_t$. If m is an odd number, apply moving average of order m, $\text{MA}(m)$, to estimate trend-cycle component $\hat{T}_t$.
Step 2: Compute the detrended series with the formulation $X_t - \hat{T}_t$.
Step 3: Calculate the average detrended values for each season to estimate the seasonal component $\hat{S}_t$. Then, the seasonal component values are adjusted to ensure that they add to zero.
Step 4: Compute the remainder component with the formulation $\hat{R}_t = X_t - \hat{T}_t - \hat{S}_t$.

Meanwhile, the procedure for performing multiplicative decomposition is as follows:

Step 1: If m is an even number, apply moving average of order 2 to moving average of order m, $\text{MA}(2 \times m)$, to estimate trend-cycle component $\hat{T}_t$. If m is an odd number, apply moving average of order m, $\text{MA}(m)$, to estimate trend-cycle component $\hat{T}_t$.
Step 2: Compute the detrended series with the formulation $X_t/\hat{T}_t$.
Step 3: Calculate the average detrended values for each season to estimate the seasonal component $\hat{S}_t$. Then, the seasonal component values are adjusted to ensure that they add to m.
Step 4: Compute the remainder component with the formulation $\hat{R}_t = X_t/(\hat{T}_t\hat{S}_t)$.

2.2 Extreme Learning Machine

ELM is an efficient learning algorithm for classification and prediction in SLFNs, the structure of ELM as shown in Figure 2. The procedures of ELM are written in this study refer to [24][26].

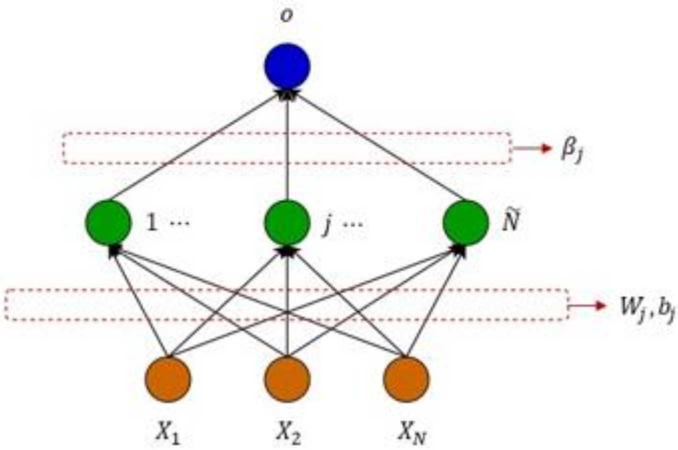

Figure 2. The Structure of ELM

Assume there are N samples (X_t, t_i), where X_i denotes the feature and t_i denotes the target value. The model of SLFNs with $\tilde{N}$ hidden nodes can be modelled as below:

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(X_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(W_i \cdot X_j + b_i) = o_j, \quad j = 1, \dots, N, \tag{3}$$

where $W_i = \left[w_{i,1}, w_{i,2}, \ldots, w_{i,\tilde{N}}\right]^T$ is the weight vector that connects the ith hidden dan the input nodes and b_i is the ith bias of hidden layer nodes, and they are initialized randomly. $\beta_i = \left[\beta_{i,1}, \beta_{i,2}, \ldots, \beta_{i,\tilde{N}}\right]^T$ is the weight vector connecting the ith hidden and output nodes and o is the output value. To minimize the error between output o_j and target t_j, which is represented as $\sum_{i=1}^{N} \|o_j - t_j\| = 0$, there is an existing optimal value of β_i such that

$$\sum_{i=1}^{\tilde{N}} \beta_i g(W_i \cdot X_j + b_i) = t_j, \qquad j = 1, \ldots, N. \tag{4}$$

Then above N equation can be written briefly as

$$H\beta = T, \tag{5}$$

where

$$H(W, b, X) = \begin{bmatrix} g(W_1 \cdot X_1 + b_1) & \cdots & g(W_{\tilde{N}} \cdot X_j + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(W_1 \cdot X_N + b_1) & \cdots & g(W_{\tilde{N}} \cdot X_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}}. \tag{6}$$

Thus, the output weight β can be written as

$$\beta = H^+ T, \tag{7}$$

where $H^+ = (H^T H)^{-1} H^T$.

2.2 Mean Absolute Percentage Error

The goodness of the model can be evaluated using forecasting error. The forecasting error used in this study is Mean Absolute Percentage Error (MAPE). The MAPE formulation is as follows:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{X_t - \hat{X}_t}{X_t} \right| \times 100\%. \tag{8}$$

Moreover, to evaluate the goodness of the model, there are objective criteria based on MAPE. In this study, we used the grades of Moreno et al. [27]; four levels of the MAPE include highly accurate (<10%), good (10%-20%), reasonable (20%-50%), and inaccurate (>50%), respectively.

3. RESULTS AND DISCUSSION

The currency inflow and outflow data for the period January 2003 until June 2020 are presented in Figure 3 and Figure 4, respectively. The plot shows that the inflow and outflow have a seasonal pattern, where data fluctuations have a fixed frequency.

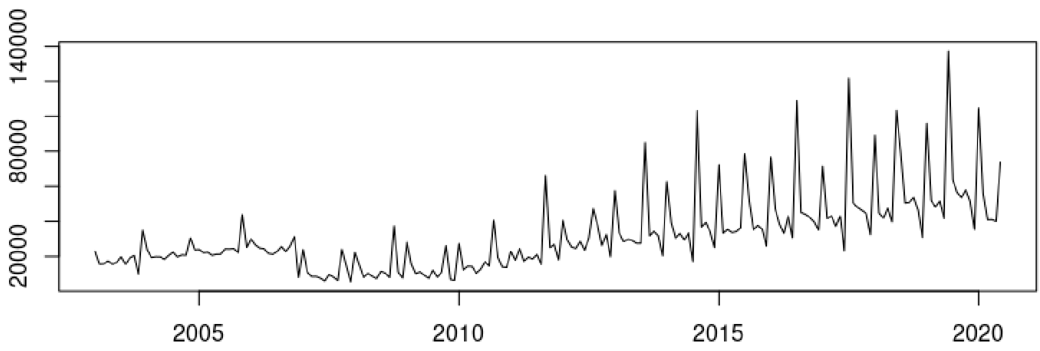

Figure 3. Time Series Plot of Currency Inflow in Indonesia (in Billion Rupiah)

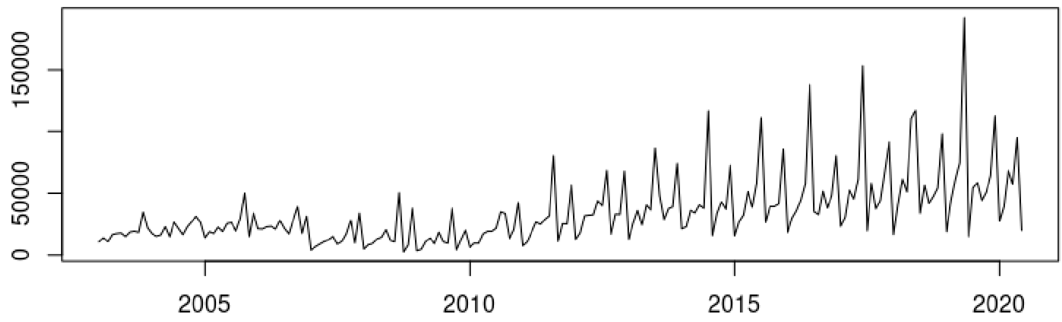

Figure 4. Time Series Plot of Currency Outflow in Indonesia (in Billion Rupiah)

Hybrid ELM model is implemented to those data. Decomposition technique is used to decompose the training data into trend-cycle, seasonal, and remainder components. Training data is set from January 2003 to December 2017, while testing data is set from January 2018 to June 2020. Because the inflow and outflow data have seasonal variations that fluctuate and appear proportional to the level of the time series, the decomposition technique used is multiplicative. After that, we applied ELM for analysis on the trend-cycle component of the training data. The forecasted results by using hybrid ELM model for currency inflow and outflow are shown in Figure 5 and Figure 6, respectively.

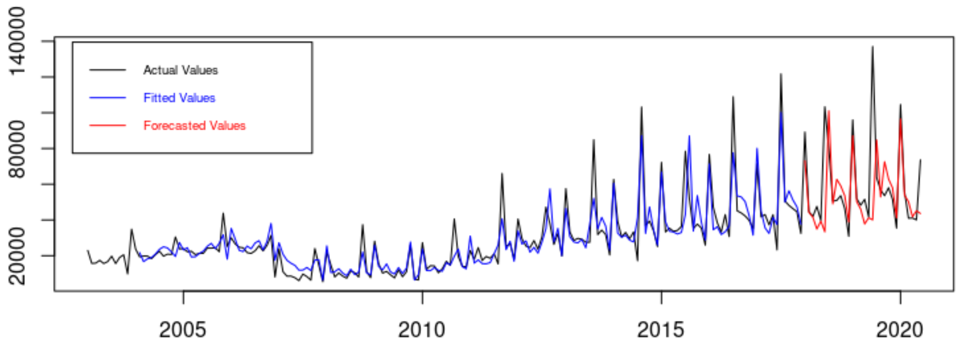

Figure 5. Forecast of Currency Inflow by Using Hybrid ELM Model

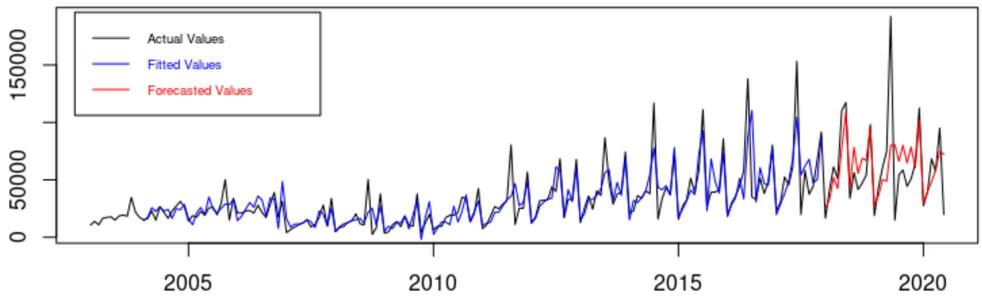

Figure 6. Forecast of Currency Outflow by Using Hybrid ELM Model

In general, Figures 5 and 6 show fitted values and forecasted values for inflows and outflows close to the actual values. However, at some points, the peaks and valleys of the data show considerable differences. To see the goodness of the hybrid ELM model accurately, the MAPE values for training and testing are calculated and presented in Table 1. In addition, to determine the effectiveness of the decomposition combined with ELM in the hybrid ELM model, the inflow and outflow forecasts will be compared with the original ELM. MAPE values of the original ELM are also presented in Table 1.

Tabel 1. MAPE Value

Model	Inflow		Outflow	
	Training (%)	Testing (%)	Training (%)	Testing (%)
Hybrid ELM	19.90	17.89	34.69	47.51
ELM	23.57	20.27	44.35	65.29

Based on Table 1, the Hybrid ELM model shows that MAPE values are smaller than ELM. Thus, the combination of decomposition techniques in ELM is known to be effective in forecasting data with seasonal variations. Following [27], for the hybrid ELM model on inflow data, the MAPE value shows that the forecasting results are categorized as good. Meanwhile, for the hybrid ELM model on outflow data, the MAPE value shows that the forecasting results are categorized as reasonable.

4. CONCLUSIONS

This study has developed a hybrid ELM model by combining decomposition and ELM techniques in forecasting currency inflows and outflows in Indonesia, which contain seasonal variations. Based on the comparison results with the original ELM, the hybrid ELM model produces forecasting values with the smallest error. Thus, it can be concluded that the hybrid ELM model can predict time series data better than the original ELM.

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