

## Forecasting the Amount of Currency in Circulation and the Volume of Electronic Money Transactions Using a Hybrid VAR-GRU Method

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### Abstract

Vector Autoregressive (VAR) is a method for forecasting multivariate time series data, but VAR is less able to represent nonlinear patterns in the data. One method in deep learning that is able to capture nonlinear patterns in data is the Gated Recurrent Unit (GRU). In hybrid VAR-GRU, a VAR model is used to model the linear component, while the residuals serve as input for a GRU to capture nonlinear patterns that the VAR model fails to explain. This study aims to predict the amount of currency in circulation and the volume of electronic money transactions using a hybrid VAR-GRU method, and to compare its performance with a single VAR model. The data used in this study are the amount of currency in circulation and the volume of electronic money transactions from January 2019 to December 2024. Subsequently, forecasting was conducted using the VAR-GRU method for the period from January to October 2025 and compared with actual data to calculate the MAPE. The results show that the hybrid VAR-GRU has better performance than single VAR model. The MAPE value obtained by the hybrid model for the volume of electronic money transactions is 4.39% and for the amount of currency in circulation is 2.93%, so the combined MAPE is 3.66%. Meanwhile, the VAR model produces a combined MAPE of 5.22%. Research results indicate that the hybrid VAR-GRU method can serve as a more accurate alternative to support cash demand planning, liquidity management, and the formulation of digital payment system policies in Indonesia.

**Keywords:** Vector Autoregressive (VAR), Gated Recurrent Unit (GRU), Hybrid VAR-GRU, Amount of Currency in Circulation, Volume of Electronic Money Transactions.

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## 1. INTRODUCTION

Time series forecasting is forecasting or predicting the value of the next period based on historical time series data [1]. Vector Autoregressive (VAR) is a time series data forecasting model developed by Christopher Sims, where all variables are treated equally, that is, they are considered endogenous variables. Each endogenous variable is explained by the lag of its own value and the other endogenous variables in the model [2]. Although VAR is capable of simultaneously modeling linear relationships between variables, it has limitations in capturing the nonlinear patterns commonly found in modern time-series data. Therefore, a deep learning-based approach capable of learning nonlinear relationships more effectively is required [3]. A Recurrent Neural Network (RNN) is a type of deep learning architecture that employs an artificial neural network specifically designed to process sequential or time series data. One type of RNN is the GRU, which is a

simpler form of LSTM. Compared to conventional RNNs, GRUs are capable of addressing the vanishing gradient problem through a gating mechanism, making them more effective at capturing long-term dependencies. Furthermore, the GRU structure is simpler than that of the LSTM, requiring fewer parameters and shorter training times without compromising predictive capability.

Time series forecasting has evolved along with technological advancements, one of which is hybrid forecasting. Hybrid methods combine two or more complementary methods [4]. In this article the hybrid VAR-GRU method was used, with the VAR model being effective in capturing linear patterns from the data and the GRU model handling nonlinear patterns. The VAR method is first applied to the data, and the VAR model residuals are then used as input for the GRU method. Subsequently, the forecasting results from both methods are combined to produce a hybrid VAR-GRU forecast.

Currency in circulation is cash, consisting of banknotes and coins, used for everyday buying and selling transactions. Electronic money is money used for transactions over the internet, involving the use of computer networks, and its value is stored digitally, either via chips or servers [5]. Forecasting the amount of currency in circulation and the volume of electronic transactions is crucial, as it is needed to ensure optimal cash availability in the community, support the effectiveness of monetary policy, and maintain the stability of the financial system and the national economy. Meanwhile, accurate projections of electronic transactions can assist in planning digital payment infrastructure, both in terms of system capacity and transaction security, and encourage financial inclusion [6]. Furthermore, according to Bank Indonesia's Payment System Statistics, the value and volume of electronic money transactions have continued to increase in recent years, driven by the digitalization of payment systems and the implementation of the Quick Response Code Indonesian Standard (QRIS). On the other hand, cash currency remains an essential means of payment, making accurate cash demand forecasting increasingly important for supporting national liquidity management.

Research using the hybrid VAR-GRU method has been conducted by [7] to perform multivariate time series forecasting on cellular network quality metrics. The results show that the VAR-GRU model provides the best performance because it is able to capture linear and nonlinear relationships compared to the VAR-LSTM and VAR-CNN models. The VAR-GRU method has also been used to forecast the transaction price of Indonesian jet fuel by [8]. The accuracy results for the VAR-GRU method were 99.4%, higher than those of VAR-LSTM, which achieved an accuracy of 98.98%. Furthermore, [9] also conducted research using the hybrid VAR-GRU method to forecast global financial markets using several stock index data and global financial variables. The final results of the study indicated that the VAR-GRU model performed significantly better than several other models. These three studies demonstrate that the hybrid VAR-GRU approach improves accuracy compared to both single models and other hybrid models. However, since these studies focused on the telecommunications network sector, fuel prices, and global financial markets, their application to Indonesia's payment systems remains very limited.

The amount of currency tends to follow a linear trend and relatively predictable seasonal patterns, while the volume of electronic transactions is more influenced by nonlinear factors such as technological innovation, regulatory changes, and shifts in consumer behavior. Therefore, researchers are interested in using a hybrid VAR–GRU model in this study because it combines the advantages of the VAR model in capturing linear patterns and the GRU model in capturing nonlinear patterns in data. In addition, until now there has not been much previous research that specifically applies the hybrid VAR–GRU model to analyze the amount of currency in circulation and the volume of electronic transactions in Indonesia, so this research also provides a new contribution to the development of digital economic forecasting methods.

## 2. LITERATURE REVIEW

### 2.1 Vector Autoregressive (VAR)

Vector Autoregressive (VAR) is a time series data forecasting model developed by Christopher Sims, where all variables are treated equally, that is, they are considered endogenous variables. Each endogenous variable is explained by the lag of its own value and the other endogenous variables in the model. The term autoregressive comes from the presence of a lag value on the right side of the equation, while the term vector comes from a vector with two or more variables [2].

For example:  $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$  denotes a vector of size  $n \times 1$  from time series variables. The VAR model with lag  $p$  can be written as follows.

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \dots + \Pi_p Y_{t-p} + \varepsilon_t, \quad t = 1, \dots, T \quad (1)$$

where:

$Y_t$  : vector of endogenous variables at time  $t$

$Y_{t-i}$  : lag  $i$  of  $Y_t$

$\Pi_i$  :  $n \times n$  coefficient matrix

$\varepsilon_t$  :  $n \times 1$  error vector

$c$  :  $n \times 1$  intercept vector

The VAR model must fulfill the stationarity test for variance and mean. The variance stationarity equation using Box-Cox is as follows.

$$T(Y_t) = \frac{Y_t^\lambda - 1}{\lambda} \quad (2)$$

where  $\lambda$  is the transformation parameter value. Data that is stationary to variance is data with a  $\lambda$  value of one. Stationarity to the mean can be determined using the Augmented Dickey-Fuller (ADF) test. The ADF test has the following equation.

$$ADF_{count} = \frac{\hat{\phi}}{SE(\hat{\phi})} \quad (3)$$

Data is stationary to the mean if  $ADF_{count} > ADF_{table}$  or  $p\text{-value} < \alpha$ . Data that is non-stationary at the initial level but stationary during the differencing process must be tested

for cointegration. If the data does not exhibit a cointegrating relationship, a VAR in differences model can be constructed. Cointegration testing can be performed using the Johansen test. Before estimating VAR parameters, it is necessary to determine the optimal lag length. The optimal lag length can be determined using the smallest Akaike Information Criteria (AIC).

$$AIC(p) = \ln|\hat{\Sigma}_p| + \frac{2k^2p}{T} \quad (4)$$

where:

$k$  : number of parameters in the model

$|\hat{\Sigma}_p|$  : determinant of the residual variance-covariance matrix

$T$  : number of observations

$p$  : order

Then the estimate of parameter  $\hat{\beta}$  is as follows.

$$\hat{\beta} = (X'X)^{-1}X'Y \quad (5)$$

Furthermore, a stability test is required to ensure that the VAR model is stable and suitable for analysis and forecasting. A VAR model is considered stable if all eigenvalues  $\lambda$  have a modulus value of less than one. The modulus value can be calculated using the following equation.

$$|\lambda| = \sqrt{(Re(\lambda))^2 + (Im(\lambda))^2} \quad (6)$$

VAR models must also fulfill the residual white noise assumption. One way to test for white noise is by using the Ljung-Box test.

## 2.2 Data Normalization

According to [10] normalization is the process of transforming the original attribute values into a specific range to better suit the needs of the analysis algorithm. This process does not create new attributes, but changes the value scale so that the model can work better. One method of data normalization is Min-Max Normalization. The Min-Max Normalization formula that changes the data scale to the range 0-1 is as follows.

$$x' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (7)$$

where:

$x'$  : normalization result

$x_i$  : normalized data

$\min(x)$  : smallest data

$\max(x)$  : largest data

### 2.3 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is part of the RNN architecture designed to address short-term memory issues and offers a simpler structure than LSTM. The GRU combines the input gate and forget gate functions of the LSTM into a single update gate, resulting in a more compact and simpler design. The GRU has four main components, that is the update gate, the reset gate, the candidate hidden state, and the final hidden state [11].

### 2.4 Hyperparameter Tuning

Hyperparameter tuning is the process of determining the best hyperparameter values for a machine learning algorithm, with the aim of maximizing the predictive performance of the model on a given data set. Random Search is a hyperparameter tuning method that searches for hyperparameter values by randomly selecting parameter combinations from a predetermined search space. The most common GRU hyperparameters obtained through the tuning process include the number of GRU units (hidden units) that determine the model's ability to learn data patterns based on time sequences, the number of epochs as the number of repetitions of the training process, the batch size that regulates the amount of data in each weight update, and the learning rate that controls the speed of the optimization process. In addition, the dropout rate is often used to reduce the risk of overfitting and the window size (time step) is used to determine the length of the input sequence in time series data [12].

### 2.5 Hybrid VAR-GRU

In the hybrid VAR-GRU method for forecasting time series data, the first stage is to apply the VAR method to the data, then use the residual results of the VAR model as input to the GRU method. After that, the results of the two methods are combined to obtain the forecast. The hybrid method equation according to [13] can be written as follows.

$$\hat{y}_t = \hat{y}_t^{VAR} + \hat{y}_t^{GRU} \quad (8)$$

where:

- $\hat{y}_t$  : predicted value of the  $t$ -th hybrid model
- $\hat{y}_t^{VAR}$  : predicted value of the  $t$ -th VAR linear component
- $\hat{y}_t^{GRU}$  : predicted value of the  $t$ -th GRU residual component

### 2.6 Model Evaluation

Model accuracy can be evaluated using various methods, one of which is the Mean Absolute Percentage Error (MAPE). According to [14], MAPE is the average absolute percentage error between the actual value and the predicted result. A smaller MAPE value indicates a lower error rate and a more accurate model. MAPE has the following equation.

$$MAPE = \frac{\sum_{i=1}^M \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{M} \times 100\% \quad (9)$$

where:

- $y_t$  :  $t$ -th actual data
- $\hat{y}_t$  :  $t$ -th predicted data
- $M$  : number of predictions made

## 2.7 Currency in Circulation

According to Bank Indonesia, currency in circulation is money owned and used by the public in conducting transactions. [15] also states that currency in circulation is money issued by the Central Bank in the form of paper money or coins. The main functions of currency in circulation include a medium of exchange, a store of value, and a unit of account. In traditional payment systems, cash is still the main instrument, especially for daily payments and for small-value transactions [5].

## 2.8 Electronic Money Transaction

Electronic money is money that is used for transactions via the internet and involves the use of computer networks, as well as balances that are stored digitally, either chips or servers [5]. Technological advancements are a major factor driving shifts in people's economic transaction patterns. This is evident in the increasing number of companies, offices, and shopping centers that accept electronic payments. Furthermore, electronic transactions are also influenced by individual behavior. [16] pointed out that the younger generation, particularly Generation Z, prefers e-wallets due to their convenience, speed, security, and attractive promotions. This indicates a shift in public preference for modern payment systems.

## 3. METHOD

### 3.1 Data

This research uses secondary data, namely the amount of currency in circulation and the volume of electronic transactions obtained from the official Bank Indonesia website. The data is a monthly time series covering the period January 2019 to December 2024.

### 3.2 Research Methodology

The research stages carried out in this study are as follows.

1. Descriptive analysis of data on the amount of cash in circulation and the volume of electronic transactions.
2. Conduct a stationarity test on the variance using Box-Cox, then transform the data that is not stationary.
3. Conduct a stationarity test on the average using the ADF test. If the data is not stationary, then perform differencing and retest the stationarity of the differencing data.
4. Stationary data in the differencing process is tested for cointegration using the Johansen test. Data that exhibits a cointegration relationship should use the VECM method, but if there is no cointegration, the VAR model can be used.
5. Determine the optimal lag based on the smallest AIC value.
6. Estimate parameters and build a VAR model using optimal lag values.
7. Calculate the residuals of the VAR model.
8. Test the stability of the VAR model.
9. Test the residual assumptions using the Ljung-Box test.

10. Forecast the next period using the VAR model.
11. Input data for the GRU model using the residual data from the VAR model.
12. Preprocess by normalizing or scaling the GRU model data.
13. Build the GRU model.
14. Forecast the residuals for the next period using the GRU model.
15. Combine the forecast results for the next period from the VAR and GRU models to create a hybrid VAR-GRU model forecast.
16. Calculate the accuracy of the VAR and hybrid VAR-GRU models by looking at the MAPE value.

## 4. RESULT AND DISCUSSION

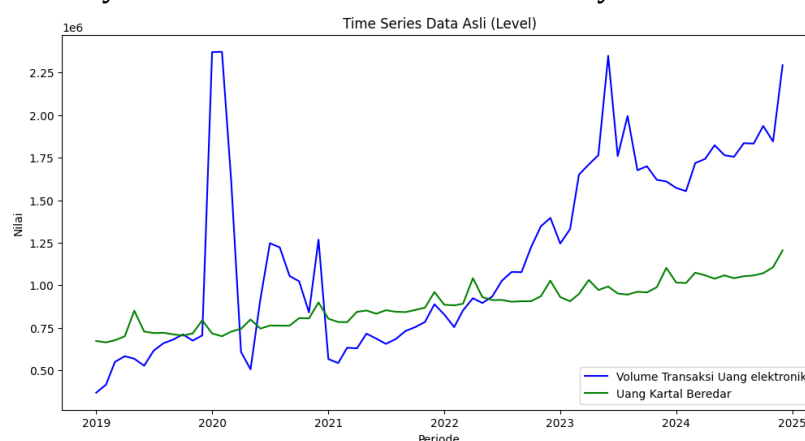
### 4.1 Descriptive Analysis

The following presents descriptive statistics for data on the amount of currency in circulation and the volume of electronic money transactions in Indonesia.

**Table 1.** Descriptive Statistics

| Statistical Measure         | Currency in Circulation<br>(Billion Rupiah) | Electronic Money Transactions<br>(Thousand Transactions) |
|-----------------------------|---------------------------------------------|----------------------------------------------------------|
| Mean                        | 883,375.358                                 | 1,177,356.456                                            |
| Standard Deviation          | 129,182.293                                 | 548,410.132                                              |
| Relative Standard Deviation | 14.62%                                      | 45.58%                                                   |
| Minimum Value               | 663,858.910                                 | 367,938.992                                              |
| 1 <sup>st</sup> Quartile    | 777,700.132                                 | 685,136.395                                              |
| Median                      | 888,181.535                                 | 1,039,716.853                                            |
| 3 <sup>rd</sup> Quartile    | 976,082.541                                 | 1,682,003.330                                            |
| Maximum Value               | 1,204,536.378                               | 2,372,349.430                                            |

Based on Table 1, the relative standard deviation of electronic money transactions is higher than that of currency in circulation. This indicates that electronic transactions experience sharper fluctuations, whereas the circulation of currency is relatively more stable. In addition to descriptive statistics, the data characteristics are also analyzed visually using time series graphs to see the movement patterns, trends, and fluctuations in circulating currency and the volume of electronic money transactions.

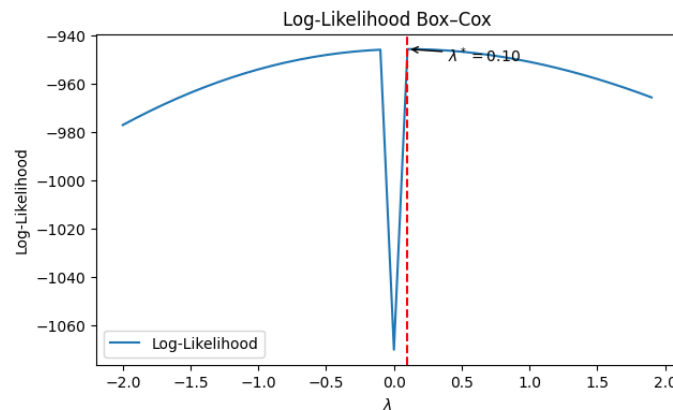


**Figure 1.** Time Series Data Chart

Figure 1 shows that currency in circulation tends to follow a relatively linear trend, characterized by gradual increases and modest fluctuations over time. Conversely, the volume of electronic money transactions exhibits a nonlinear pattern, characterized by sharp fluctuations, periodic spikes, and inconsistent growth. These conditions underlie the use of the hybrid VAR-GRU model.

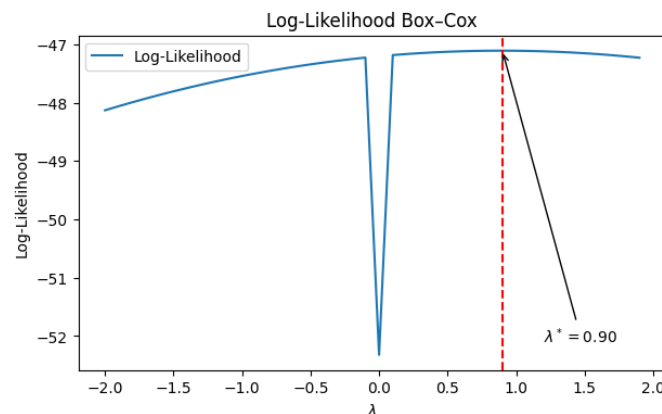
## 4.2 Stationarity

Stationarity of variance will be tested using the Box-Cox method. The analysis results for the electronic money transaction volume variable can be seen in the following graph.



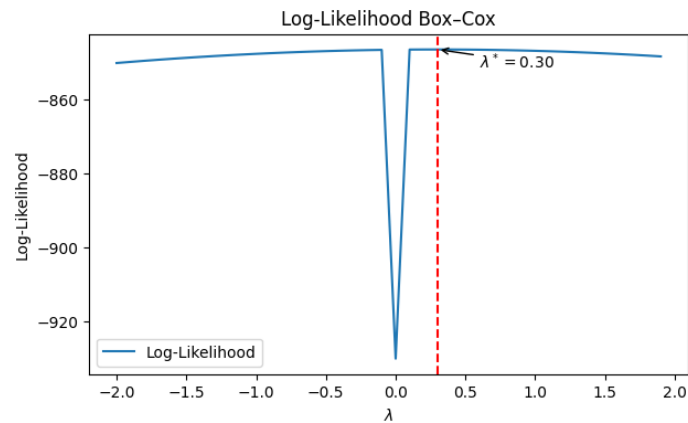
**Figure 2.** Box-Cox Chart of Electronic Transaction Volume

In Figure 2 above, the  $\lambda$  value obtained is 0.1. Because the  $\lambda$  value is still far from one, a Box-Cox transformation is performed. The following is the graph after the transformation.



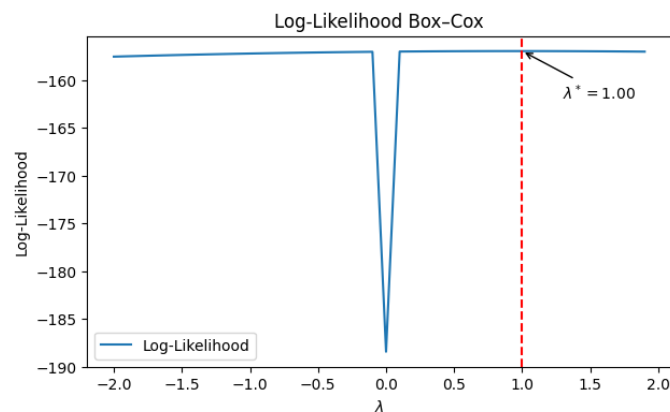
**Figure 3.** Box-Cox Chart of Electronic Transaction Volume after Transformation

Based on the graph after transformation, the  $\lambda$  value obtained is 0.9. A  $\lambda$  value approaching 1 indicates that the current data form is stationary to variance, so additional transformation is not necessary. The Box-Cox graph for the currency in circulation variable can be seen in the following graph.



**Figure 4.** Box-Cox Chart of Currency in Circulation

In Figure 4 above, the  $\lambda$  value obtained is 0.3. Because the  $\lambda$  value is still far from one, a Box-Cox transformation is performed. The following is the graph after the transformation.



**Figure 5.** Box-Cox Chart of Currency in Circulation after Transformation

Based on the graph after transformation, the obtained  $\lambda$  parameter value is 1. This indicates that the transformed data does not require further transformation or that the data variance is stationary. Furthermore, data that has met stationarity to variance will be tested for stationarity to the mean using the ADF test.

**Table 2.** ADF Data Level Test Results

| Variable                      | ADF Statistic | <i>p-value</i> |
|-------------------------------|---------------|----------------|
| Currency in Circulation       | 0.007         | 0.959          |
| Electronic Transaction Volume | -1.287        | 0.635          |

Based on Table 2, the *p-value* for both data sets is greater than the significance level, indicating that the data is non-stationary. Because it does not meet the stationarity test, differencing is performed.

**Table 3.** ADF Test Results after Differencing

| Variable                      | ADF Statistic | <i>p-value</i> |
|-------------------------------|---------------|----------------|
| Currency in Circulation       | -2.933        | 0.042          |
| Electronic Transaction Volume | -6.574        | 0.000          |

Based on Table 3, the p-value obtained for both data is smaller than the significance level, so the data is stationary. Once the data has undergone transformation and differencing and satisfies the requirements for variance and mean stationarity, subsequent testing can be performed.

### 4.3 Cointegration

Cointegration testing is required in the VAR method to determine the existence of a long-term relationship between two or more time series datasets that are individually non-stationary. A VAR model can be used if no cointegration relationship exists. The cointegration test in this research was carried out using the Johansen test.

**Table 4.** Johansen Test Results

| $\lambda_{trace}$ | Critical value $\alpha = 5\%$ |
|-------------------|-------------------------------|
| 11.044            | 15.494                        |

Based on Table 4, it is obtained that  $\lambda_{trace} < critical\ value$ , so this means that the number of cointegration vectors is zero, or there is no long-term relationship between the two variables. Since there is no cointegration relationship, the VAR model can be applied to this data.

### 4.4 Determining Optimal Lag

The optimal lag is determined by looking at the smallest AIC value. The AIC values obtained using Python software are presented in the following table.

**Table 5.** AIC Values

| Lag | AIC   |
|-----|-------|
| 0   | 2.613 |
| 1   | 2.621 |
| 2   | 2.558 |
| 3   | 2.357 |
| 4   | 2.412 |
| 5   | 2.505 |
| 6   | 2.520 |

Based on Table 5, the smallest AIC value obtained was at lag 3. So the optimal lag is lag 3 and the VAR model formed is the VAR(3) model.

### 4.5 VAR Model

Estimation of the VAR model using the OLS method produces the following parameter estimates  $\hat{\beta}$ .

$$\hat{\beta} = (X'X)^{-1}X'Y = \begin{bmatrix} 1.103 & 0.119 \\ -0.518 & -0.004 \\ -0.432 & -0.05 \\ -0.461 & 0.029 \\ 0.052 & -0.214 \\ -0.324 & 0.025 \\ -0.38 & -0.388 \end{bmatrix}$$

So the VAR equation model is obtained as follows.

$$\begin{aligned}
y_{1t} &= 1.103 - 0.518y_{1,t-1} - 0.432y_{2,t-1} - 0.461y_{1,t-2} + 0.052y_{2,t-2} - \\
&\quad 0.324y_{1,t-3} - 0.38y_{2,t-3} + \varepsilon_{1t} \\
y_{2t} &= 0.119 - 0.004y_{1,t-1} - 0.05y_{2,t-1} + 0.029y_{1,t-2} - 0.214y_{2,t-2} + 0.025y_{1,t-3} - \\
&\quad 0.388y_{2,t-3} + \varepsilon_{2t}
\end{aligned}$$

#### 4.6 Stability Test

After obtaining a VAR model with optimal lag, a stability test is carried out to ensure that the model formed is stable and suitable for use in further analysis.

**Table 6.** VAR Stability Test Results

| Modulus            |
|--------------------|
| 0.7326122795209342 |
| 0.7326122795209342 |
| 0.7806696057749138 |
| 0.7806696057749138 |
| 0.6429803135856025 |
| 0.6429803135856025 |

Based on Table 6, all modulus values are less than one, so the VAR model is stable and good for further analysis, specifically for forecasting purposes in this study.

#### 4.7 Residual White Noise Assumption Test

The residual white noise assumption test was carried out using the Ljung-Box test.

**Table 7.** Ljung-Box Test Results

| Variable                      | <i>p-value</i> |
|-------------------------------|----------------|
| Currency in Circulation       | 0.592          |
| Electronic Transaction Volume | 0.971          |

Based on Table 7, the p-value obtained for both variables is more than the significance level, which means that the residual currency in circulation and the volume of electronic transactions are white noise or there is no autocorrelation in the residuals. Residuals exhibiting white noise characteristics indicate that the information contained in the data has been successfully explained by the model, leaving no autocorrelation patterns. Thus, the model satisfies one of the key assumptions for generating accurate forecasts.

#### 4.8 Forecasting with VAR Model

The forecasting results of the VAR model are as follows.

**Table 8.** VAR Model Forecasting Results

| Period        | The Amount of Currency in Circulation Forecasting | Electronic Money Transactions Volume Forecasting |
|---------------|---------------------------------------------------|--------------------------------------------------|
| January 2025  | 1,141,842.365                                     | 2,338,878.788                                    |
| February 2025 | 1,137,451.951                                     | 2,463,682.864                                    |
| March 2025    | 1,147,729.482                                     | 2,334,879.712                                    |
| April 2025    | 1,185,546.730                                     | 2,309,264.670                                    |
| May 2025      | 1,180,679.120                                     | 2,355,760.709                                    |

|                |               |               |
|----------------|---------------|---------------|
| June 2025      | 1,182,715.857 | 2,520,445.757 |
| July 2025      | 1,189,340.005 | 2,608,134.433 |
| August 2025    | 1,204,891.489 | 2,614,484.328 |
| September 2025 | 1,211,020.929 | 2,604,361.651 |
| October 2025   | 1,217,553.751 | 2,660,198.092 |

The forecasting results using the VAR model in Table 8 indicate an upward trend in the amount of currency in circulation and the volume of electronic money transactions during the prediction period. However, the VAR model captures only linear patterns, meaning it may still yield prediction errors when applied to data exhibiting nonlinear characteristics.

#### 4.9 Residual Data Normalization and Building GRU Model

Before building the GRU model, the residual data is normalized using Min-Max Normalization because the VAR residual data still has a non-uniform value scale. The normalized VAR residual data will be formed into a scale of 0 to 1. Next, the normalized VAR model residuals are used as input to the GRU model. To obtain optimal model performance, a hyperparameter tuning process is carried out to determine the best parameter combination. In this study, hyperparameter tuning was carried out with the help of Python software using the Random Search method. The following are the best hyperparameters produced.

**Table 9.** Best Hyperparameter

|               |        |
|---------------|--------|
| Units         | 32     |
| Learning rate | 0.0005 |
| Dropout       | 0.1    |
| Batch Size    | 8      |

The best hyperparameters based on Table 9 are then used in GRU model training to produce a final model that is ready to be used in the forecasting stage.

#### 4.10 GRU Residual Forecasting

Residual forecasting with GRU for the next 10 periods with the help of Python software using Jupyter Notebook is obtained as follows.

**Table 10.** GRU Residual Forecasting Results

| Currency in Circulation | Electronic Money Transactions |
|-------------------------|-------------------------------|
| -0.537                  | -0.341                        |
| -0.222                  | 0.034                         |
| 0.012                   | 0.111                         |
| 0.148                   | 0.121                         |
| 0.226                   | 0.115                         |
| 0.258                   | 0.102                         |
| 0.264                   | 0.089                         |
| 0.264                   | 0.08                          |
| 0.256                   | 0.072                         |
| 0.248                   | 0.066                         |

The residuals from the GRU forecasting in Table 10 represent the nonlinear components that the VAR model failed to capture. These residual values are subsequently added to the VAR forecasting results to generate a hybrid prediction.

#### 4.11 Forecasting with Hybrid VAR-GRU Model

The hybrid model forecast is obtained by summing the VAR model forecast and the GRU residual forecast.

**Table 11.** Hybrid VAR-GRU Forecasting Results

| Period         | The Amount of Currency in Circulation Forecasting | Electronic Money Transactions Volume Forecasting |
|----------------|---------------------------------------------------|--------------------------------------------------|
| January 2025   | 1,132,529.808                                     | 2,161,421.082                                    |
| February 2025  | 1,124,346.862                                     | 2,295,425.089                                    |
| March 2025     | 1,134,743.617                                     | 2,231,546.357                                    |
| April 2025     | 1,174,892.217                                     | 2,269,900.178                                    |
| May 2025       | 1,174,049.893                                     | 2,377,750.252                                    |
| June 2025      | 1,180,660.128                                     | 2,603,787.729                                    |
| July 2025      | 1,191,998.540                                     | 2,749,134.572                                    |
| August 2025    | 1,212,359.558                                     | 2,806,390.597                                    |
| September 2025 | 1,223,186.681                                     | 2,841,604.572                                    |
| October 2025   | 1,234,322.909                                     | 2,945,582.771                                    |

Table 11 presents the forecasting results obtained using the VAR-GRU hybrid model for the period of January–October 2025. These predictions were generated by combining the linear component of the VAR model with the nonlinear component derived from residual prediction using GRU. The model's accuracy is subsequently evaluated in the model evaluation subsection using MAPE values.

#### 4.12 Model Evaluation

The VAR model produces MAPE for each variable, namely 7.58% for the volume of electronic transactions and 2.87% for the amount of currency in circulation, so that the combined MAPE of the two variables for the VAR model is 5.22%. While the hybrid VAR-GRU model produces MAPE for each variable, namely 4.39% for the volume of electronic transactions and 2.93% for the amount of currency in circulation, so that the combined MAPE of the two variables for the VAR model is 3.66%.

### 5. CONCLUSION

Based on the results of research on forecasting the amount of currency in circulation and the volume of electronic money transactions using the hybrid VAR-GRU method, several conclusions can be obtained, namely the combination of the VAR-GRU method has been proven to be able to capture different data characteristics, namely a relatively linear trend pattern in currency in circulation and nonlinear fluctuations in the volume of electronic money transactions, in addition, based on the results of the model evaluation, the hybrid VAR-GRU model shows better performance than the single VAR model. The MAPE value

obtained by the hybrid model for the volume of electronic money transactions is 4.39% and for the amount of currency in circulation is 2.93%, so the combined MAPE is 3.66%. Meanwhile, the VAR model produces a combined MAPE of 5.22%. This indicates that the hybrid approach is able to significantly improve forecasting accuracy.

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