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Determination of the Optimal Model on Money Supply Data in Indonesia Using Backpropagation Neural Networks

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ABSTRACT

Inflation is a very important economic indicator, the rate of growth is always kept low and stable so as not to cause macroeconomic diseases which will later have an impact on economic instability. The money supply is an indicator that influences the inflation rate, so that the government can control the inflation rate by stabilizing the amount of money in circulation through the monetary policy of Bank Indonesia. The purpose of this research is to predict the amount of money using a backpropagation neural network model, to know the level of accuracy of the model and to predict the money supply in the future. The optimal model of the money supply obtained from the application of the backpropagation neural network is *ANN BP(12,6,1)*. The modeling accuracy obtained from the optimal model of ANN *BP(12,6,1)* is 92.47% or with a *MAPE value* of 7.53%. The *BP(12,6,1)* model is categorized as a model that has very good forecasting capabilities, so it is appropriate to be used as a reference model for forecasting data on the amount circulating in Indonesia in the future.

Keywords : Model, Money Supply, Artificial Neural Network, Backpropagation

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1. INTRODUCTION

Money is a necessity in driving the economy of a country. Even money, which at first was only used as a medium of exchange, has now turned into a multi-function. When money is considered as capital, then money will become personal goods or personal property, where people can store, hoard and deposit money from distribution and circulation in society. Therefore, the role and function of money with itself shifts from being a medium of exchange to being a means of storing value of wealth.[1][2]

According to Sutawijaya (2012) the money supply in Indonesia has a positive effect on inflation. That is, if the money supply increases, inflation will also follow this increase directly. This indicates that the money supply affects the rate of inflation in Indonesia. While inflation is one of the economic indicators that must always be maintained stability. This is because some of the impacts caused by inflation such as investment will decrease, poverty will increase, corruption will increase, and various other problems. So that the amount of money in circulation has an important role in controlling the inflation rate in Indonesia through the monetary policy held by Bank Indonesia.[3][4]

According to information from the Coordinating Ministry for Economic Affairs of the Republic of Indonesia (www.ekon.go.id) that amid the pandemic, Indonesia's inflation was relatively controlled compared to several countries which continued to experience increasing inflation due to supply-demand imbalances and the energy crisis, Singapore for example was 3. 8% (yoy), Euro Area 4.9% (yoy) and United States 6.8% (yoy) in November 2021.

In the midst of inflationary pressures in various developed countries, Indonesia's inflation rate in 2021 is still under control at a low and stable level, and is below the set target range of 3.1% (yoy). Realized inflation in 2021 was recorded at 1.87% (yoy) or an increase from the realization in 2020 which was 1.68% (yoy). The results of this control cannot be separated from the strong coordination between the Central Government, Regional Governments and Bank Indonesia in maintaining price stability.

Based on the information provided by the Coordinating Ministry for Economic Affairs of the Republic of Indonesia, it can be stated that inflation in Indonesia is currently still in a stable condition. However, it cannot be denied that Indonesia will also experience extreme fluctuations in inflation in the future, whether it is influenced by the level of demand for money by the public or other factors which are also factors causing inflation in Indonesia. So in this case the government needs to consider one of the strategies that can be applied to maintain inflation stability, especially in terms of monetary policy (money control). One of the strategies that the authors offer in this study is to do data modeling. According to identify a component, modeling is very important because it can provide understanding and make predictions in the future. The modeling used in this study is modeling the money supply in Indonesia using the backpropagation neural network method.[5][6]

2. LITERATURE REVIEWS

Research on the money supply in Indonesia was conducted by Rosyidah et al. (2018) uses the Vector Autoregressive With Exogenous Variable (VARX) method. The purpose of this study is to obtain a model for predicting the amount of currency, the amount of quasi-money and the number of securities other than stocks. The results of his research obtained the VARX(1,1) model with very good ability and the MAPE value of the amount of currency was 7.54%, quasi money was 0.49%. Subsequent research was carried out by Achmalia et al., (2020) with the title "Forecasting Cement Sales Using Backpropagation Neural Networks and Recurrent Neural Networks". The purpose of this study was to obtain BPNN and RNN modeling of the Elman type for forecasting cement sales at PT Semen Indonesia (Persero) Tbk, as well as forecasting results using the best model. The results of this study produce the best model for forecasting cement sales at PT Semen Indonesia (Persero) Tbk, namely the BPNN model (9-5-1) with an accuracy rate of 87.97%. The error obtained is 12.07%, meaning that the method used has good capabilities.[7][8]

Figure 1 is a flowchart of a backpropagation artificial neural network

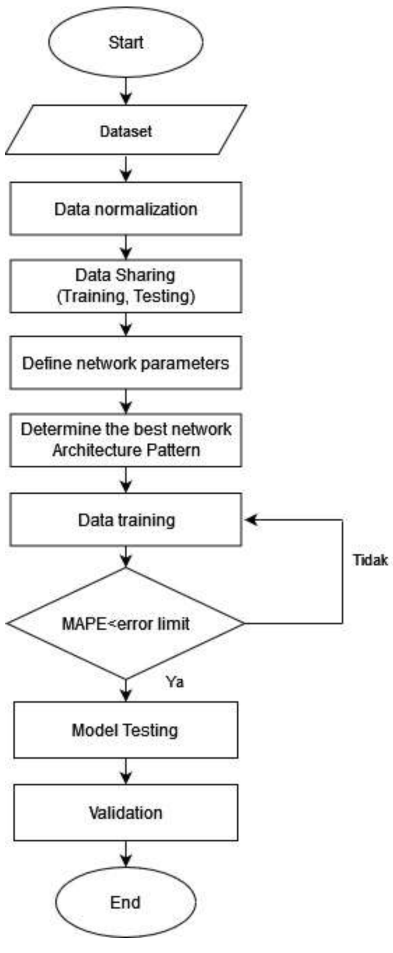

Figure 1. Artificial Neural Network Flowchart

3. EXPERIMENTAL

The type of research used is applied research with a quantitative approach. The data used in this study is secondary data obtained from the publication of the Central Bureau of Statistics, namely monthly data on the amount of money in circulation in Indonesia from January 2010 to June 2022. Based on the data pattern, the time series is divided into two, namely linear time series and nonlinear time series. One method that is very flexible in forecasting or modeling time series data containing linear and nonlinear patterns is a neural network. The advantage of using a neural network is the flexibility of the model which can be formed adaptively based on the features presented from the data.[9][10]

The data analysis technique used is money supply data modeling using an Artificial Neural Network with a short-term Backpropagation algorithm. Artificial neural network is a method that has a fairly low data error rate and is quite good in the generalization process because it is supported by sufficient training data and a learning process that adjusts the weights so that this model is able to predict time series data for several future time periods. This artificial neural network modeling is dynamic and real time. The type of artificial neural network used is *backpropagation*.

Backpropagation is supervised learning, meaning that the results obtained from the process of applying this backpropagation must be similar to the training pattern being tested. Neural network training is basically done through presenting a set of examples of input value patterns and their associated output targets (expectations). Each hidden and output neuron processes its input by multiplying each input by its weight, summing the products and then passing the sum through a nonlinear transfer function to produce a result. This backpropagation neural network has 3 layers namely input layer, hidden layer and output layer. The activation function used is a binary sigmoid with a value range of 0.1 to 0.9 because it has an accompanying asymptomatic nature. The following is the mathematical model equation of the *backpropagation* [11].

$$y_t = w_0 + \sum_{j=1}^{p} w_j \cdot g\left(v_{oj} + \sum_{I=1}^{n} v_{ij} \cdot y_{t-1}\right) + \varepsilon_t \tag{1}$$

The steps that must be followed in determining the optimal model of the Artificial Neural Network are as follows.

a. Understanding stage

Preparing the dataset that will be used in this study by looking at the mean, minimum data, maximum data, median and movement patterns of the monthly data on the amount of money in circulation in Indonesia from January 2010 - June 2022.

b. Data preparation stage: Data normalization and data sharing (*Train and Test).*

First, normalizing the monthly money supply in Indonesia from January 2010 - July 2022 to match the Binary Sigmoid activation function (0.1) with equation (2). [12][13]

$$y_t = \frac{0{,}8(x_t - \min(x))}{\max(x) - \min(x)} + 0{,}1 \tag{2}$$

Second, the stage of dividing data into two groups, namely training data (data training) of 78%, namely from January 2010 to December 2019 and data testing (data testing) of 22%, namely from January 2020 to June 2022. The data is divided into training data for get the model and test data to evaluate the goodness of the model. The goodness of forecasting is highly dependent on the test data used to evaluate the goodness of the model. This process is called holdout validation [14][15].

c. Modeling Stage: Determining Parameters and Network Architecture

First, determining the training parameters used, namely using the Mean Absolute Percentage Error (MAPE) performance function with equation (3), determining the maximum epoch (repetition) of training performed on the data, determining the learning rate, and determining the error limit.

Second, define architecture artificial neural network, namely the number of units of the input layer, hidden layer and output layer.

d. Backpropagation Algorithm Training Phase [16][17]

- Step 0: Initialize the weights randomly (choose a small random value between 5 and -5).
- Step 1: If the stopping condition is not met, do steps 2 – 9
- Step 2: for each pair of training data, do steps 3 – 8
- Step 3: Feedforward Phase.

  Each input unit () $x_i, i = 1, 2, 3, \ldots, n$)receives an input signal $x_i$and forwards this signal to all units in the layer in front of it, namely the hidden layer.
- Step 4: Every unit in the hidden layer ($z_j, j = 1, 2, 3, \ldots, p$)add up with:

  $$z\_in_j = v_{oj} + \sum_{i=1}^{n} x_i v_{ij}$$

  Compute the output signal using the binary sigmoid activation function. Then forward this signal to the layer in front of it, namely the output layer.

  $$z_j = f(z\_in_j) = \frac{1}{1 + e^{-z\_in_j}}$$
- Step 5: For each output unit ($y_k, k = 1, 2, 3, \ldots, m$), add up the input signal weight values:

  $$y\_in_k = \sum_{j=1}^{p} z_j w_{jk} + w_{ok}$$
- Compute the output signal using the binary sigmoid activation function.

$$y_k = f(y\_in_k) = \frac{1}{1+e^{-y\_in_k}}$$

- Step 6: Backpropagation of Error Phase. Calculate the error value (δ)at each output unit ($y_k, k = 1,2,3,\dots,m$),

  $\delta_k = (t_k - y_k)f'(y\_in_k) = (t_k - y_k)\, f(y\_in_k)\, [1 - f(y\_in_k)]$
- Calculate the change in weight values $w_{jk}$and bias weights w_{ok}. Then propagate the error value (δ_k) to the unit layer below it, namely the hidden layer

  $\Delta w_{jk} = \alpha\delta_k z_j; \Delta w_{ok} = \alpha\delta_k$
- Step 7: Calculate the error value for each hidden unit $(z_j, j = 1,2,3,\dots,p)$

  $$\delta_j = \delta\_in_j f'\left(z\_in_j\right) = \sum_{k=1}^{m} \delta_k w_{jk}\, f'\left(z\_in_j\right) = \sum_{k=1}^{m} \delta_k w_{jk}\, f(z\_in_j)\, [1 - f(z\_in_j)]$$

  Calculate the increase in the hidden layer weight value and the bias weight value:

  $\Delta v_{ij} = \alpha\delta_j x_i; \quad \Delta v_{oj} = \alpha\delta_j$
- Step 8: Make changes to all the weights between the hidden layer and the output layer

  $w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$

  $w_{0k}(new) = w_{0k}(old) + \Delta w_{ok}$
- Make changes to the weight values for all weights between the input layer and the hidden layer

  $v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$

  $v_{0j}(new) = v_{0j}(old) + \Delta v_{oj}$
- Step 9: The training process stops when the number of cycles of changing the weight (epoch) during training has reached the maximum or the resulting error is smaller than the specified error.

e. Evaluation Stage (Denormalization and Validity)

Denormalization is returning data values that have been normalized to the form of data before normalization. The mathematical equation of the data denormalization is as follows:

$$\frac{(y_t - 0{,}1)(\max(x) - \min(x))}{0{,}8} + \min(x) = x'_t \tag{3}$$

Calculating the error of a forecast is also known as calculating accuracy measures or forecasting model validation. Validation is done to find out whether the model used for forecasting is good or not. The size of the forecasting error can be calculated by measuring the forecasting error, namely the Mean Absolute Percentage Error (MAPE). The model uses predictive data to get the Mean Absolute Percentage Error using equation (4). If the model validation value (MAPE) is between 10-50%, the model is suitable for use in research according to the provisions in table 1 [18][19].

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \tag{4}$$

The MAPE value can be used as a measurement material regarding the goodness of the model in forecasting by looking at the error value it produces [19][20]. The MAPE value interval is shown in Table 1 below.

Table 1. MAPE Value Interval

MAPE	Significant
$< \mathbf{10}$ %	Forecasting ability is very good
$\mathbf{10-20}$ %	Good forecasting ability
$\mathbf{20-50}$ %	Decent forecasting ability
$> \mathbf{50}$ %	Poor forecasting ability

f. Utilization Stage

When the artificial neural network model has achieved optimal results as expected, this model will become a reference for forecasting data on the Amount of Money in the future.

4. RESULTS AND DISCUSSION

The main information from data on the money supply from January 2010 to June 2022 such as the mean, median, lower quartile (Q1), upper quartile (Q3) is very necessary in a study so that researchers can find out data patterns formed from research data. The following is the money supply data presented with a boxplot.

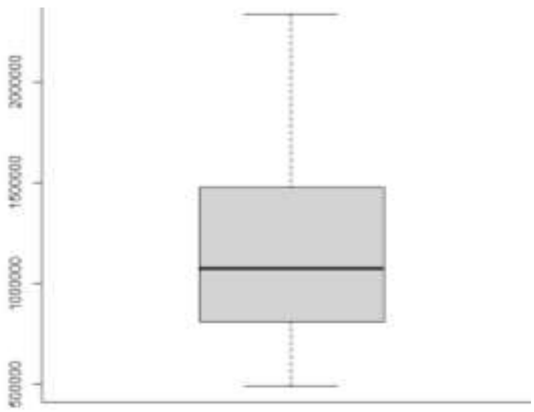

Figure 1. Boxplot The Money Supply in Indonesia (Billions)

Figure 1. shows the distribution (distribution) of money supply data illustrated by a boxplot. The minimum value of this boxplot is around IDR 490,000 billion, while the maximum value is around IDR 2,330,000 billion. The median value of this data is IDR 1,076,975 billion. Judging from the shape of the boxplot that is formed, it can be stated that the data on the money supply is more stretched upward (right) as evidenced by the length of the upper line (right) being longer than the length of the line below (left). This means that data on the money supply is more concentrated on the left. It is also marked by the distance between the lower quartile (Q1) and the median (Q2) which is shorter than the upper

quartile (Q3) and the median (Q2). Data on the money supply has experienced a more massive increase starting from 2019 to 2022. The following is data on the money supply from January 2010 to June 2022.

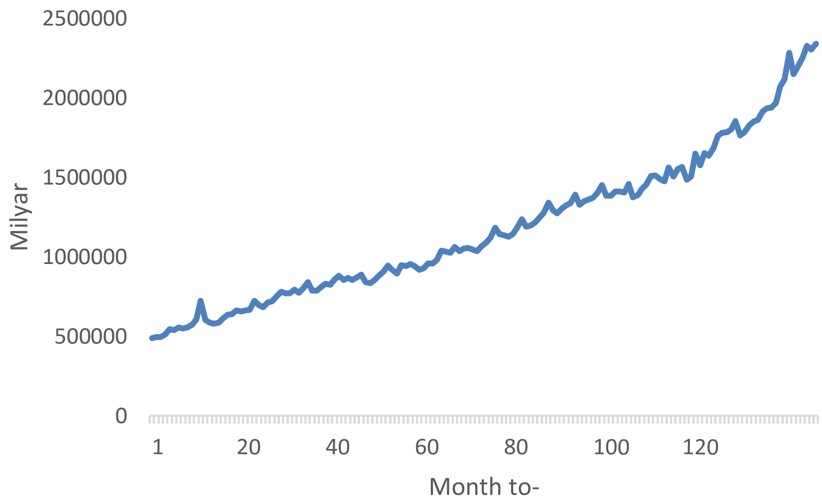

Figure 2. Money Supply from January 2010 until June 2022

Figure 2. shows that the money supply from January 2010 – June 2022 has a nonlinear pattern making it very suitable for the application of the artificial neural network method in determining the optimal model in this study. The optimal ANN model will later be used for forecasting in the future. Data on the money supply in Indonesia has a trending (increasing) pattern from year to year starting from January 2010 – June 2022 due to the influence of many factors, such as population, level of population welfare, trade market, interest rates, and patterns of society/government in carrying out each function.

Based on the figure, there were several points where the money supply increased very sharply so that it is very likely that the money supply also influenced the inflation rate that occurred in that period. Starting from 2020 there was a significant increase in the money supply from the previous year, with a difference of IDR 2,350 billion. This increase can be said to be large, because the increase in previous years was only around IDR 1,000 billion - IDR 1,800 billion. Meanwhile, the difference in the increase in the money supply in 2020 and 2021 is IDR 3,144 billion, higher than the previous year. This increase is most likely due to the impact of the pandemic, starting from the initial discovery of patients who were exposed to the *Corona Virus* (Covid 19) in Indonesia to the stage of restoring all systems that were once chaotic in Indonesia.

Data on the money supply used in this study must be in the range of 0 to 1 (should not be below 0.1 and exceed 0.9). The range of data values adjusts to the activation function used, namely the Binary Sigmoid activation function. So that the money supply data must first go through the normalization process to obtain the expected range of values. The following is the result of data on the money supply from January 2010 to June 2022 which has been normalized with *R software* .

Table 2. JUB Data Normalization Results

Date	JUB
29/01/2010	0.10000
28/02/2010	0.10189
29/03/2010	0.10200
29/04/2010	0.11035
⋮	⋮
29/04/2022	0.89470
29/05/2022	0.88419
29/06/2022	0.90000

Table 2. shows the results of normalized data on the money supply in Indonesia, which is in the range of 0.1 and 0.9. After the data is normalized, the next step is to share the data, namely training *data* and testing *data* . The proportion of *training data* is 78% of the overall data without randomization because it is a time series data. The *training* data totaled 108 data from January 2010 to December 2019. Meanwhile, the *testing data consisted* of 30 data or 22% of the total data, from January 2020 to June 2022.

At the stage of determining the network architecture, it was found that the number of *input layer units* used in this study was 12 units, based on the number of months in one period (year). So that the unit *input layer* $(x_i, i = 1,2,3, \dots, 12)$ to be used is 12 with $(y_{t-1} + y_{t-2} + \cdots + (y_{t-12})$. Meanwhile, the determination of the number of *hidden layer units* is carried out by using a *trial and error technique* because there are no standard rules governing the optimal number of *hidden layers* in an artificial neural network. The number of *output layer units* used is one unit because it only consists of one variable. The maximum epoch used is 1x10 ^{6} , the learning rate is 0.2, and the *error limit* is 0.001. The combination of these parameter values is selected based on the speed of computation and the small *error* that is generated. The following is the result of modeling the artificial neural network generated from the artificial neural network.

Table 3. Neural Network Model .

BP(n,p,m)	*MAPE (%)*	Epoch
12-1-1	2,922	3041
12-2-1	2,491	513
12-3-1	2,476	573
12-4-1	2,630	584
12-5-1	1,838	692780
12-6-1	1,719	254224
12-7-1	2,254	227
12-8-1	2,419	645
12-9-1	2,397	426
12-10-1	2,384	249

Table 5 shows several models of artificial neural networks that use a different number of *hidden layers* in order to find the most optimal ANN model. The models tested in the modeling stage totaled 10 *backpropagation network models* . Based on these models, there is one *backpropagation network model* with the smallest *MAPE* (*error*) value of 1.719%. The model is obtained from the *BP(12-6-1) network* with 12 *input layer* units, 6 *hidden layer* units and 1 *output layer unit* . While the modeling accuracy obtained is 98.74%. Furthermore, the magnitude of the epoch (repetition) obtained by the *BP(12-6-1)* model is 254224 repetitions. The following is a comparison of the MAPE values obtained by 10 artificial neural network models.

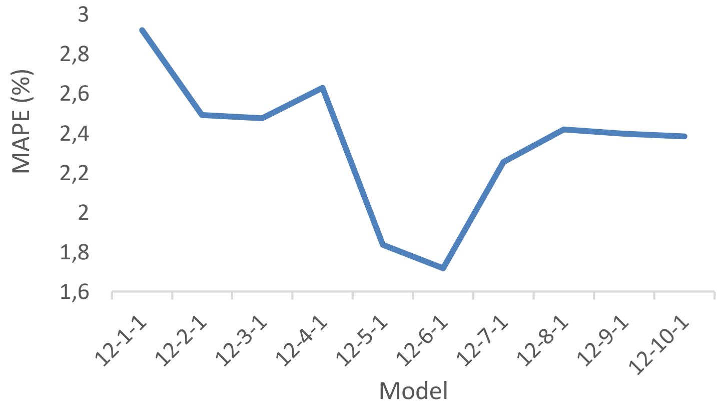

Figure 3. Comparison of MAPE values

Figure 3. above shows that the smallest MAPE value is obtained by the *BP(12,6,1) ANN model* with errors ranging from 1.6% to 1.8%. This value is considered very small so that the *BP(12,6,1) ANN model* belongs to the category of models that have very good forecasting abilities if forecasting is done for several periods in the future.

Next is to test the *BP(12,6,1) ANN model* by utilizing the test data that has been previously divided, totaling 30 data. This test was conducted to find out how optimal the *BP(12,6,1) ANN model* can predict future data. Following are the results of testing the *ANN model BP(12,6,1)* .

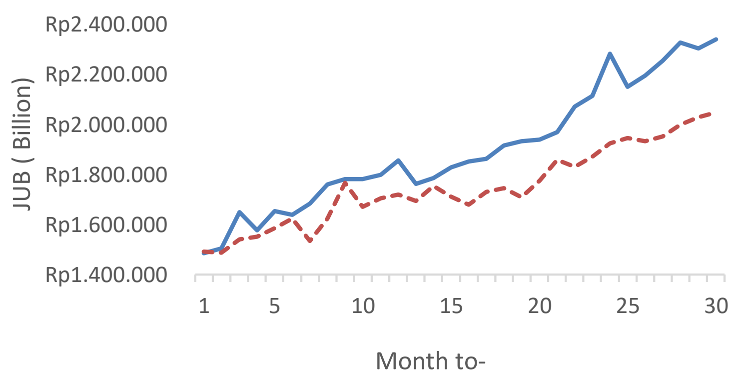

Figure 4. JUB Test Results January 2020 to June 2022

Figure 4. shows that the predicted data pattern formed has a slightly farther distance between the predicted value and the actual value in the test data. This means that the *error* obtained in the test is greater than in the training process. This is because the *BP(12,6,1) ANN model* memorizes too much the shape of the pattern produced in the *training process* , so it is a little difficult to recognize data patterns in the prediction process. Even so, the results of forecasting with the *BP model (12,6,1)* have a small *MAPE* of 7.53%, meaning that the *BP ANN network (12,6,1)* has very good forecasting capabilities with an accuracy of 92.47%.
The following is a mathematical model of an artificial neural network as follows:

$$y_t = w_0 + \sum_{j=1}^{6} w_j \cdot g\left(v_{oj} + \sum_{i=1}^{12} v_{ij} \cdot y_{t-1}\right) + \varepsilon_t$$

5. CONCLUSION

Based on the research results obtained, several conclusions are obtained as follows.

1. The optimal model generated by the application of the Backpropagation algorithm on the money supply data in Indonesia is BP(12,6,1).
2. The optimal model accuracy for ANN BP(12,6,1) on training data is 98.29% with a MAPE value of 1.71%. While the accuracy of the validity of the model obtained on the testing data is 92.47% with a MAPE value of 7.53%. The BP(12,6,1) model is categorized into a model that has a very high forecasting ability. This is evident from the error value which is below 10%. So it can be stated that the BP(12,6,1) artificial neural network model is very feasible to be used as a reference for predicting data on the amount circulating in Indonesia in the future.

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