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Backpropagation on Neural Network Method for Inflation Rate Forecasting in Indonesia

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Abstract

Inflation is the increase of prices of goods that can affect other prices of goods. Inflation is a main economic problem often faced by society. This economic problem could cause detrimental economic, political, and social effects. Inflation can be caused by a variety of sources. One of them comes from imported goods. Therefore, forecasting is needed to find out the inflation rate in the future. Inflation forecasting can be used to prepare government policies to keep inflation at a low level. In addition, the forecasting results can also be utilized by all members of the society. This study proposed the Backpropagation Neural Network method to forecast the inflation rate in the future. This study used time-series data of inflation rate and CPI (Consumer Price Index). The tested data resulted in a forecast. The RMSE (Root Mean Square Error) technique was used to test the accuracy of the forecasting results. This study also implemented the Sugeno FIS model as a comparison method. The result showed that the performance of the proposed method is better than the comparison method with an RMSE value of 0.204.

Keywords: *Inflation Rate Forecasting, Backpropagation Neural Network, Sugeno FIS, RMSE (Root Mean Square Error).*

1 Introduction

A problem that continuously receives government attention is the problem of inflation. Inflation is a main economic problem often faced by society. Inflation is an economic phenomenon in the form increasing price levels [1]. Increasing price levels will affect the prices of other goods. This economic problem can cause detrimental economic, political, and social effects. Inflation can result from the rising prices of imported goods. Inflation will happen if imported goods which increase in price have a very important role in the expense activities of a company. An example is the effect of increasing oil prices to economies of other countries that import oil. Oil is essential in the production process of industries. Therefore, increasing oil prices will increase production costs, and the increasing production costs result in the increase of prices. The high increase of oil prices may cause inflation problems. To find out the inflation rate of a country, an inflation indicator is used, called the Consumer Price Index (CPI) [2]. Changes in the Consumer Price Index that occur from time to time show the price movement of goods and services consumed by society.

Forecasting is an activity to predict what will happen in the future. Inflation forecasting can be used to prepare government policies to keep inflation at a low level. Also, the inflation forecasting results can also be utilized by the society. Inflation can increase the price of commodities so that farmers can earn huge sales from their agricultural products. In addition, the forecasting results can be used as an indicator for investment. When forecasting results show a high inflation rate, the investment value will increase, especially investment in property that will give benefit to the investors.

Forecasting is done based on historical data with time-series analysis. Time-series analysis is done based on previous months where increasing inflation happened. Historical data with time-series analysis is widely used in several studies related to forecasting. One of them is the application of the Sugeno Fuzzy Inference System model [3]. The inflation forecasting in this study will involve CPI as the external factor that affects the inflation rate. CPI measures a set of specific items prices such as staple foods, clothing, housing, and variety of goods and services purchased by consumers. Historical data and CPI are considered as input data, and the output data is the inflation rate in the future [4].

Successful studies in inflation rate forecasting include the studies conducted by Moser et al. [5] and Baciu [6]. Moser et al. [5] used the Auto Regression Integrated Moving Average (ARIMA) to predict the inflation rate. Baciu used stochastic models to predict the inflation rate. Both of these studies have several weaknesses, one of which is that in predicting the inflation rate, it is not enough to use historical data; some external factors affect the inflation rate, like macroeconomic factors. In terms of forecasting, a Neural Network (NN) can be used to predict the non-linear variables [7]. A NN has a good learning ability and can easily adapt to its environment. A NN is able to find out the knowledge patterns in any distribution of data including data that are very irregular and capricious [8]. Chen and Zhang mentioned that a NN can approximate accuracy, but requires a lot of training data[9].

In another study, the NN method was successfully used by Sadimon and Haron [10] for predicting facial caricature landmark configurations. To evaluate the NN method, the MSE (Mean Square Error) analysis was used. The accuracy of the resulting system using 6 hidden neurons was equal to 1.06185. From the test results it could be concluded that the NN method is an appropriate method used to predict the inflation rate in the future with data distribution that is irregular and capricious. Forecasting using the NN method has shown some advantages, which include ease of operation and acceleration of the learning process.

2 Literature Study

Some previous studies have conducted inflation rate forecasting. Baciu [6] was successful in predicting inflation rate by using stochastic models. Baciu compared some processes in stochastic models, where the results from each processes were compared. The purpose of this study was to identify and determine which process would give the best forecasting result. The results of this study produced good forecasting. However, each step of the experiments in stochastic models only produced the estimation of the actual system characteristics for certain input parameters. In addition, stochastic models required a long time to become more developed.

Moser et al. [5] used the factor model proposed by Stock and Watson [11] as well as VAR and ARIMA models to generate 12-month out-of-sample forecasts of inflation and its Austrian HICP sub-indices. The results showed that the factor model had the highest accuracy. Moser et al. mentioned that the accuracy could be further enhanced by combining the information contained in the model factors and VAR model for some indices.

Puspita and Yulianti [12] used fuzzy logic for weather forecasting. The fuzzy logic model used of them is the Takaghi-Sugeno-Kang Fuzzy Inference System. Their study aimed to implement the Sugeno FIS model for testing the accuracy of weather forecast results. The inputs used in this study were temperature, humidity, and wind. It was found that the Sugeno FIS can be used for forecasting with an accuracy above 60%.

A study conducted by Somaratna et al. [13] showed that a Neural Network was more suitable for forecasting problems. Sadimon and Haron [10] used a Neural Network to forecast a facial caricature configuration for a given original face image. This study also explained the data preparation process that proposed Procrustes superimposition methods derived from a NN dataset. Testing was conducted to compare Procrustes superimposition methods that were modified with the original and to find an appropriate structure of a NN to produce accurate forecasting results. To measure the accuracy of the system, this study used the MSE technique, where the accuracy produced was equal to 1.06185 with 6 hidden neurons.

Kuok et al. [14] used a Neural Network to predict hourly runoffs at different times in a small watershed. The NN method was used in this study in order to avoid the subjectivity factors of a conceptual simulation model. The input data used in this study was rainfall data. The results of the study were evaluated using correlation coefficients and the peak error technique. The results showed that the performance of a NN could simulate runoffs per hour with a high accuracy. Therefore, the forecasting results could be used as a warning to take protective action before floods.

3 The Dataset

In this study, a dataset in the form of inflation rate data in Indonesia was used. This data came from Bank Indonesia [15] with a range from July 2005 to December 2013. The data were in the form of historical data which would be processed using the time-series analysis technique. The data processing was done to determine the data to be used on each of the input variables, which were from the previous month, from the previous two months, and from the previous three months. This study also used an external factor that can affect the inflation rate, which was the Consumer Price Index (CPI). CPI was selected because this external factor affected the inflation rate as in the previous study that has been done by Ibarra [16]. This external factor was also used as an additional input variable. CPI data was obtained from the Indonesian Central Statistics Agency (BPS) in the same range. Table 1 shows an example of data with time-series analysis. Initialization of the input variables is shown in Table 3.

Table 1: Dataset with time-series analysis

Months	Actual	*m-1*	*m-2*	*m-3*	CPI
Dec-13	8.38	8.37	8.32	8.4	146.84
Nov-13	8.37	8.32	8.4	8.79	146.04
Oct-13	8.32	8.4	8.79	8.61	145.87
Sep-13	8.4	8.79	8.61	5.9	145.74
Aug-13	8.79	8.61	5.9	5.47	146.25
Jul-13	8.61	5.9	5.47	5.57	144.63
Jun-13	5.9	5.47	5.57	5.9	140.03
May-13	5.47	5.57	5.9	5.31	138.6
Apr-13	5.57	5.9	5.31	4.57	138.64
Mar-13	5.9	5.31	4.57	4.3	138.78
Feb-13	5.31	4.57	4.3	4.32	137.91
Jan-13	4.57	4.3	4.32	4.61	136.88
Dec-12	4.3	4.32	4.61	4.31	135.49
Nov-12	4.32	4.61	4.31	4.58	134.76

4 Forecasting Using the Sugeno FIS

Forecasting becomes a basis for anyone in planning a long-term activity. Fuzzy logic was introduced by Zadeh in 1975 [17]. The Sugeno Fuzzy Inference System

(FIS) is a Fuzzy Logic model that is often used in forecasting problems. In this study, the Sugeno FIS was used as a comparison method. Some researchers use the Sugeno FIS because it is simpler in the computing process. The Sugeno FIS was used in this study as a comparison method to a Neural Network. The Sugeno FIS had been successfully implemented in some of the issues related to classification, control, and forecasting [17].

Several stages are performed in the process of inflation forecasting using the Sugeno FIS, which are fuzzification, fuzzy inference rules, and defuzzification, as shown in Fig.1 [18].

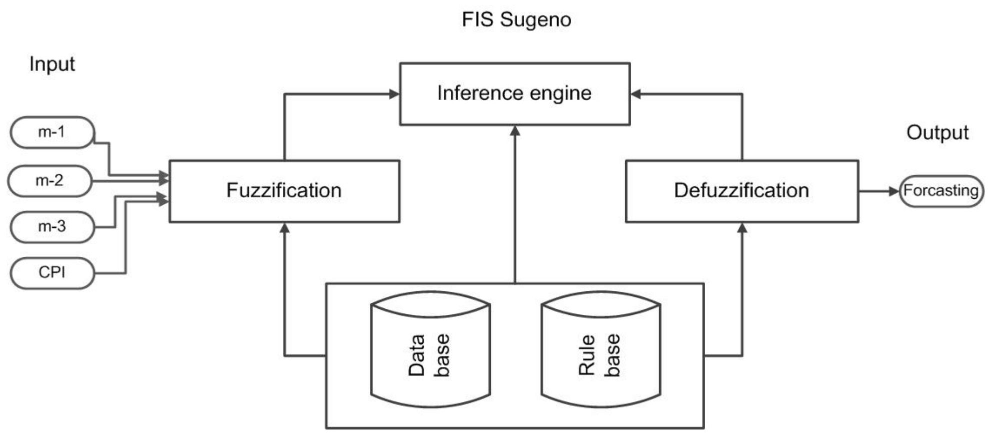

Fig.1: A general scheme of a Sugeno fuzzy inference system.

4.1 Fuzzification

In the early stage of the Sugeno FIS, fuzzy sets are established. The fuzzy set in each input variable are divided into two or more fuzzy sets [19]. This study used three input variables derived from the data from Bank Indonesia, which were from the previous month, from the previous two months, and from the previous three months. Each input variable was divided into three fuzzy sets that were the same; they were UP [0-10], CONSTANT [5-15] and DOWN [10-20] as shown in Fig.2. Each fuzzy set had a membership function that had been determined previously. The function to determine the membership function is illustrated by the curve shoulder. As for the external factor of CPI, it was divided into two fuzzy sets as shown in Fig. 3. These external factors had the domains of UP [100-300] and DOWN [100-250].

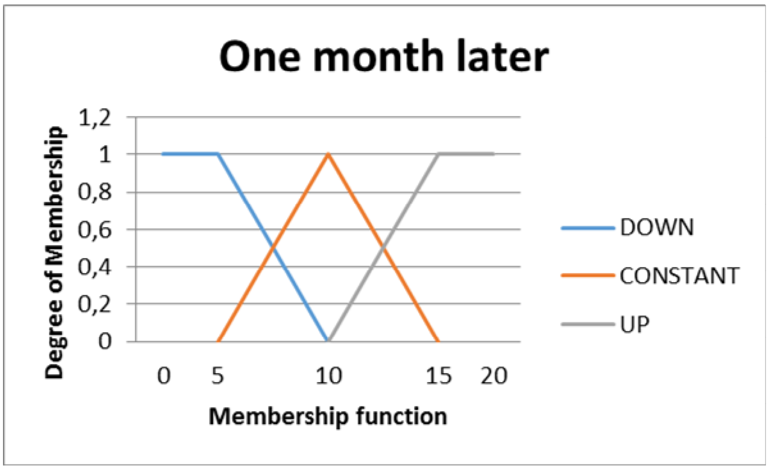

Fig.2: Membership function in input variable

The membership functions on each set are defined in Equation 1, Equation 2, Equation 3, and Equation 4.

$$\mu\ DOWN\ (x) = \begin{cases} 1 & x \leq 5 \\ \dfrac{10 - x}{5} & 5 < x < 10 \\ 0 & x \geq 10 \end{cases} \quad (1)$$

$$\mu\ UP\ (x) = \begin{cases} 0 & x \leq 10 \\ \dfrac{x - 10}{5} & 0 < x < 15 \\ 1 & x \geq 15 \end{cases} \quad (2)$$

$$\mu\ CONSTANT\ (x) = \begin{cases} 0 & (x \leq 5)\ and\ (x \geq 15) \\ \frac{x-(-5)}{5} & 5 < x < 10 \\ \frac{15-x}{5} & 10 < x < 15 \\ 1 & x \geq 10 \end{cases} \quad (3)$$

$$\mu\ DOWN\ (x) = \begin{cases} 1 & x \leq 150 \\ \dfrac{250 - x}{100} & 150 < x < 250 \\ 0 & x \geq 250 \end{cases}$$

$$\mu\ UP\ (x) = \begin{cases} 0 & x \leq 150 \\ \dfrac{x - 150}{100} & 150 < x < 250 \\ 1 & x \geq 250 \end{cases} \quad (4)$$

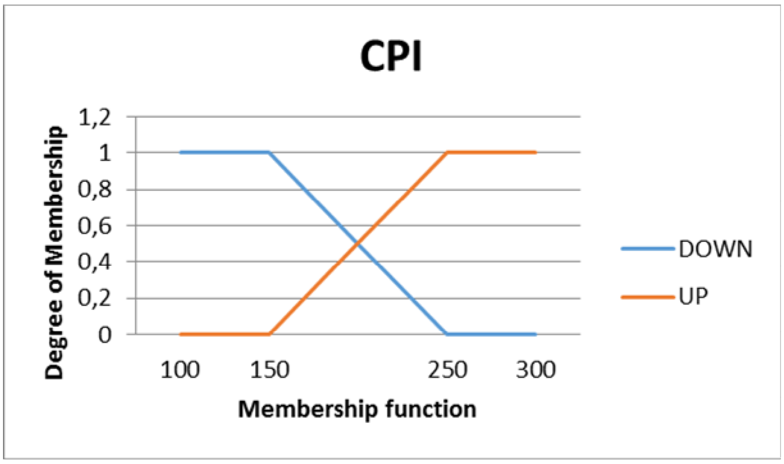

Fig.3 Membership function in input variable

4.2 Fuzzy Inference Rules

The results of the calculation process for fuzzy membership values were then inferred with the fuzzy rules. In the Sugeno method, the implication function used is MIN [19]. The basic rule in the Sugeno method is in the form of IF-THEN with order 1, where IF in the form of fuzzy sets is the antecedent and THEN in the form of a linear regression equation is the consequent. The number of rules used in this study was 29 rules. The calculation of the number of rules was to increase the number of fuzzy sets to the number of input variables. The establishment of rules is formulated in Equation 5.

$$[R_i]\ IF\ (V_1\ is\ A_1)^{\circ}\ (V_2\ is\ A_2)^{\circ} \ldots ^{\circ}\ x_n\ is\ A_n\ THEN\ z_n = q + p_1 * V_1 + \cdots + p_n * V_n \tag{5}$$

Ri : the ith fuzzy rule (i=1…n)

V_n : the nth parameter

A_n : the fuzzy set in the nth parameter that is relevant to the nth rule

Z_n : the nth linear equation

q : coefficient in consequent

p_n : the nth constants

^{o} **:** operator AND

Some examples of rules that were used in this study are shown in Table 2.

Table 2: The example of rules used in this study

R*n*	Fuzzy rules
R_1	IF *m-1* is down AND *m-2* is down AND *m-3* is down AND icp is down THEN *Zn* = a + b_1 *m-1* + b_2 *m-2* + b_3 *m-1* + b_3 *icp*
R_2	IF *m-1* is down AND *m-2* is up AND *m-3* is constant AND icp is up THEN *Zn* = a + b_1 *m-1* + b_2 *m-2* + b_3 *m-1* + b_3 *icp*
R_3	IF *m-1* is up AND *m-2* is constant AND *m-3* is down AND icp is up THEN *Zn* = a + b_1 *m-1* + b_2 *m-2* + b_3 *m-1* + b_3 *icp*
R_4	IF *m-1* is ascending AND *m-2* is up AND *m-3* is up AND icp is up THEN *Zn* = a + b_1 *m-1* + b_2 *m-2* + b_3 *m-1* + b_3 *icp*

4.3 Defuzzification

Defuzzification is a remapping process of the fuzzy values into clear values that become the solution values of the problems. In this study, the output obtained was in the form of numbers. The establishment of a rule basis was used to find the value of *α-predicate* depending on the operator and the implication functions used. The AND operator with the MIN implication function was used to find a minimum value on every rule to obtain the value of *α-predicate* as formulated in Equation 6. α_n is the *α-predicate* value on the n^{th} rule, μ_n is the degree of membership on the n^{th} rule, and x_n is the n^{th} parameter.

$$\alpha_n = \alpha_{A_1 \cap A_2 \cap \ldots \cap A_n} = \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2), \ldots, \mu_{A_n}(x_n)) \quad (6)$$

Having obtained the value of α_n, next came the process of calculating the value of each consequent of each rule (z_i) in accordance with the membership function used. This study used the Centre Average Defuzzyfier as formulated in Equation 7 [19].

$$Z = \sum_{i=1}^{n} \alpha_i z_i \quad \frac{\sum_{i=1}^{n} \alpha_i z_i}{\sum_{i=1}^{n} \alpha_i} \quad (7)$$

By using the Sugeno Fuzzy Inference System method, the accuracy was obtained to be 0.203961692. This value was obtained by using the RMSE (Root Mean Square Error) technique. RMSE was used to find how many errors were generated using a model. Fig. 4 shows a rather good movement using the Sugeno FIS model.

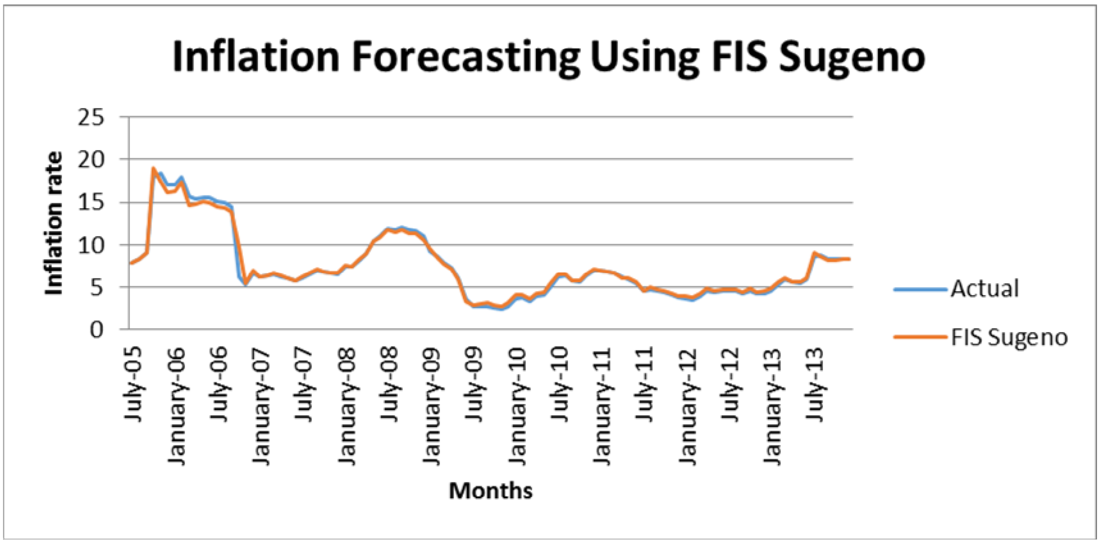

Fig. 4: The Sugeno FIS method shows a good movement for forecasting inflation rate

5 Consideration on the Neural Network Modeling

At the beginning, we decided to use the Neural Network model in this study. The Neural Network model used in this study was Back propagation, because of its simplicity of implementation. The study by Zhang and Li [4] used Back propagation as a forecasting method. The Back propagation model is a Neural Network model that consists of an input layer, a hidden layer, and an output layer.

In this study, the input layer was in the form of input data that consisted of historical data from the previous month, from the previous two months, and from the previous three months. The historical data were processed using time-series analysis in order to create the time-series data pattern. The external factor that was used in this study was CPI data, which was also used as input data. The data were used as input parameters or variables in this study. The hidden layer used in this study consisted of a hidden layer with 3 nodes (neurons). The output layer used in this study consisted of an output in the form of forecasting results. Table 3 shows the input parameters that were used in this study.

Table 3: Input parameters

Parameter	Description
m-1	From previous month
m-2	From previous two months
m-3	From previous three months
CPI	Consumer Price Index

Based on the input variables and output variables previously described, a Back propagation Neural Network model structure used in this study can be formed. The Back propagation model structure used in this study is shown in Fig.5 [14].

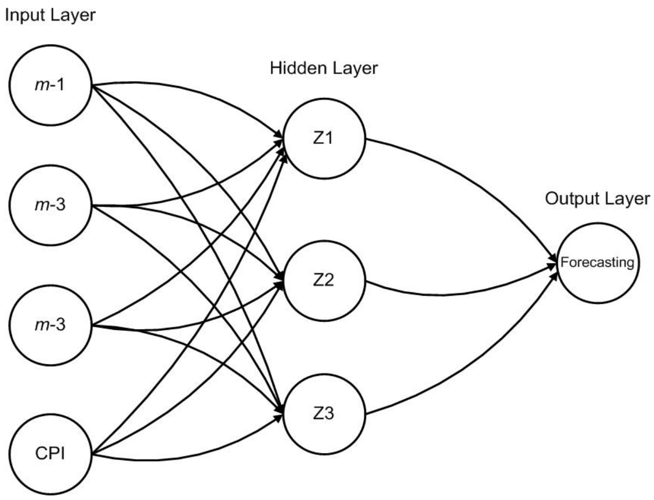

Fig. 5: The Structure model of the back propagation neural network used in this study.

6 Forecasting Inflation Using NN

To implement the back propagation neural network in inflation rate forecasting, input data in the form of the inflation rate data were required which were divided into several input variables as shown in Table 3. The data were in the form of historical inflation rate data using time-series analysis. After the input data was determined, then we determined the training data and testing data that would be used. Training data and testing data were different data. They were for the random determination of the initial weights. The training data process was carried out to produce a neural network that converged. Training was stopped if the epoch had reached a certain amount, or an error was created that reached a threshold value that was determined. The neural network would continue to be modified during the training process until the ideal network to be used was obtained. After having obtained the ideal network during the training process, data testing using predetermined testing data was complete.

The back propagation learning algorithm consisted of two processes, feed forward and back propagation of error. During the feed forward process, each input unit received (X) or the outside input signal, then the signals were propagated through each unit in the hidden layer (Z). Each hidden unit calculated according to their activation function, and then sent that signal to each unit in the output layer. After that, it would also be calculated according to the activation functions which would generate an output signal as a network response with the administration of the input pattern.

On the return of propagation, each output unit was compared to the calculated Y activation with a target value t to obtain an error. Based on this error, the value of k would be calculated; then, the value of error at the output unit would be propagated backwards to each unit in the hidden layer. Furthermore, the error was used to fix the weighting factor between output units and the hidden unit. Then, the hidden error from the output was found in order to fix the weighting factor between the input units.

The following are the detailed steps:

Step 1: Initializing a weighing factor (random)

Step 2: Repeating steps 3 through 9 until the condition was met

Step 3: Performing steps 3 through 8 for each pair of training data

<u>Feed forward</u>

Step 3: Each input unit ($X_i, i = 1,2, \dots, n$) received an input signal X_i and that input signal was propagated to the top unit of the hidden units.

Step 4: Each hidden unit were summed with the weighing factor as in Equation (8).

$$Z\_in_j = V_{oj} + \sum_{i=1}^{n} X_i V_{ij} \tag{8}$$

This was then calculated according to the activation function using a sigmoid function as in Equation (9).

$$Z_j = \frac{1}{1 + EXP^{-Z\_inj}} \tag{9}$$

Step 5: Each output unit ($\boldsymbol{Y_i, i = 1, 2, \ldots, n}$) were summed with the weighing factor shown in Equation (10).

$$Y\_in_k = W_{ok} + \sum_{j=1}^{v} Z_j W_{jk} \tag{10}$$

This was then calculated according to the activation function using a sigmoid function as in Equation (11).

$$Y_k = \frac{1}{1 + EXP^{-Y\_ink}} \tag{11}$$

<u>Back Propagation Error</u>

Step 6: Each output unit $(Y_k, k = 1, 2, \ldots, n)$ received the target pattern appropriate to the input pattern during training and error calculation.

$$E_k = (t_k - Y_k)Y_k \tag{12}$$

The weighing factor correction was calculated as in Equation (13).

$$\Delta W_{jk} = \alpha\ \delta_k \tag{13}$$

Step 7: Each output unit ($Z_j, j = 1, 2, \ldots, n$) added their delta input.

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k W_{jk} \tag{14}$$

Then, it was multiplied by the derivative of the activation function to calculate the error.

$$\delta_j = \delta\_in_j\ (Y_{in_j}) \tag{15}$$

The correction weights used to improve weight *Vij* were calculated as in Equation (16).

$$\Delta V_{oj} = \alpha \delta_j \tag{16}$$

Step 8: Each improved output unit $(Y_k, k = 1, 2, \ldots, n)$ and the weights $(j=0,1,\ldots,n)$ were calculated as in Equation (17).

$$V_{jk}(new) = V_{jk}(old) + \Delta V_{jk} \tag{17}$$

Step 9: Discharge condition test.

To predict the inflation rate using Back propagation, the data used was divided into two parts. The data was divided into training data and testing data. In a previous study [13] [7] [20] [21], training data used 70% of all data. All data used in this study were organized into 70 records. Thus, this study used 20 records for the testing data and 50 records for the training data (20:50). Fig. 7 illustrates the distribution of data for the training and testing processes.

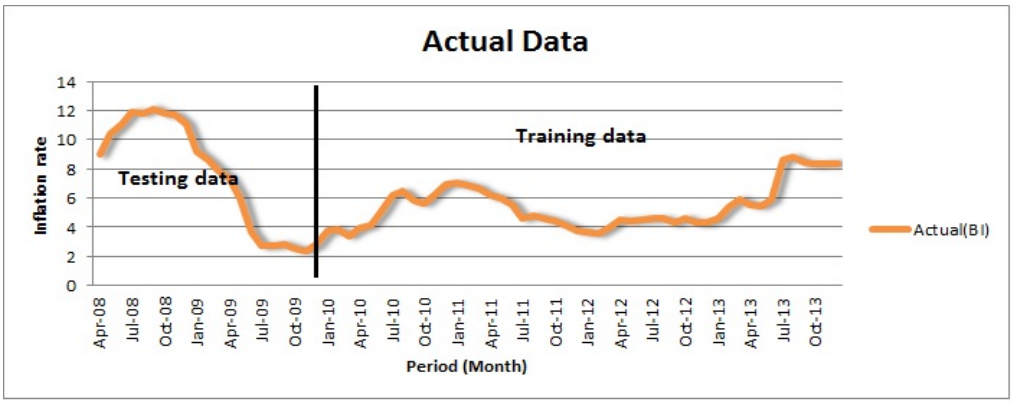

Fig.7: Tesing data and training data (20:50).

6.1 Numerical Example

In predicting the inflation rate in Indonesia, an appropriate learning rate should be determined in order to produce a more optimal system performance so that better forecasting results can be obtained. Therefore, a test to find the appropriate learning rate was needed. This test used the 50 data records for the training process. The data were taken from November 2009 to December 2013. This training data was used in testing to find the appropriate learning rate. In the training process, there were two stages: feed forward and back propagation. Feed forward was used to produce the output network in the form of forecasting results. The propagation stage was used to generate an error. Table 4 shows the test results of learning rate with 100 epochs. This study used a PC with a 32-bit operating system.

Table 4 : Learning rate testing

No.	Learning rate α	Epoch	RMSE
1	0.1	100	0.133896932
2	0.3	100	0.133896932
3	0.2	100	0.133896933
4	0.4	100	0.133896934
5	0.5	100	0.133896934
6	0.6	100	0.133896934
7	0.7	100	0.133896934
8	0.8	100	0.133896934
9	0.9	100	0.133896934

Based on the test results in Table 4, it could be seen that the appropriate learning rate was $\alpha = 0.1$. The selection of learning rate was based on the calculation of RMSE (Root Mean Square Error) which was equal to 0.133896932. Fig. 7 shows a movement graph of the smallest error content in learning rate $\alpha = 0.1$. The results of this test were used as the basis for further data testing using the testing data.

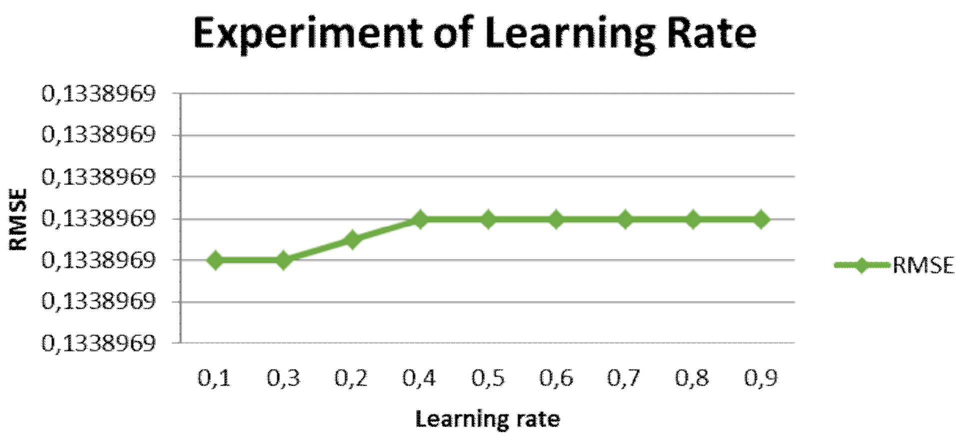

Fig. 7: The learning rate test chart

6.2 Data Examination

Based on the learning rate testing that was done in the section Numerical Example, $\alpha = 0.1$ and epoch = 100 were used as references for the data testing process. The data testing used 20 records, from March 2008 to October 2009. For the determination of weight in the data testing process, weight was determined by taking the final weight in the data training process. In the data testing process, the only stage in the neural network that was used was the feed forward network to produce an output network in the form of forecasting results. Forecasting results are shown in Table 5. Fig. 7 shows the significant movement. The graph moved closer to the actual data.

Table 5 : Testing data result

Months	Actual	Forecasting using NN	Error
October-09	2.57	2.561	2.861006673
September-09	2.83	2.9788	3.17880203
August-09	2.75	2.721	3.124907796
July-09	2.71	2.612	2.912325667
June-09	3.65	3.422	3.422470944
May-09	6.04	6.01	5.86608155
April-09	7.31	7.28	7.192052803
March-09	7.92	7.836	7.73684342
February-09	8.6	8.931	8.431810185
January-09	9.17	9.872	9.537180603
December-08	11.06	11.013	10.64255102
November-08	11.68	11.744	11.34439996
October-08	11.77	11.822	11.34444461
September-08	12.14	12.38	11.84610901
August-08	11.85	11.87	11.47310678
July-08	11.9	11.833	11.73333271
June-08	11.03	10.954	10.85488396
May-08	10.38	10.145	10.44563151
April-08	8.96	8.9	8.990007758
March-08	8.17	8.176	8.276993486
	RMSE		0.203961692

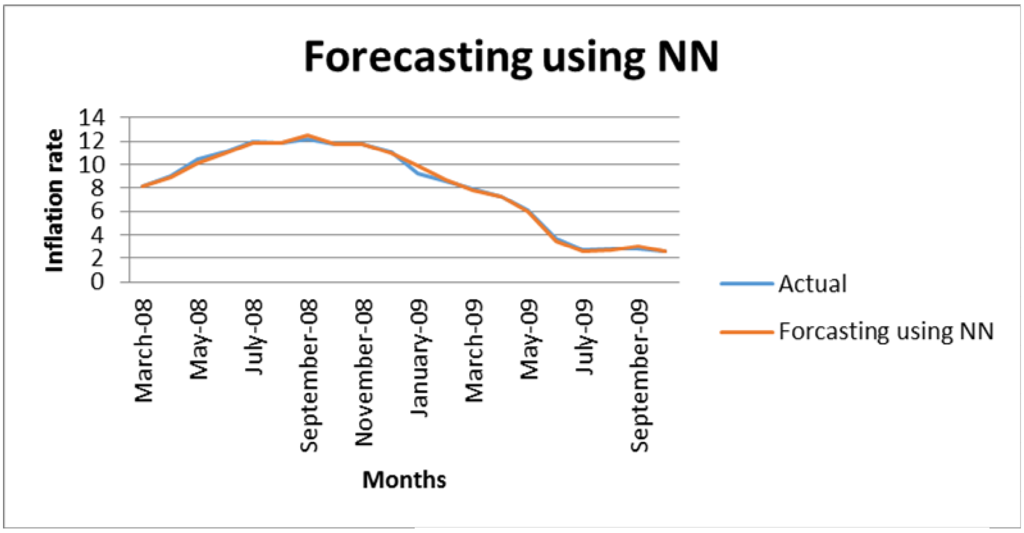

Fig.7: Forecasting using NN. The graph shows the movement of the actual approach of data

7 Result and Discussion

This study used time-series analysis to determine the input variables used which were based on historical data of inflation rates. In Section 5, an appropriate learning rate was obtained, which was $\alpha = 0.1$ with epoch=100. The learning rate was tested to produce the lowest error during the data training process. Having obtained the appropriate learning rate value of á = 0.1, the value was used as a reference for data testing. In this section, data testing was conducted with the 20 records of the time range from March 2008 to October 2009.

Table 6 shows a comparison of the inflation rate forecasting between the Sugeno FIS and the proposed neural network method. The graph in Fig. 8 shows that the Neural Network was closer to the actual data. To assess the accuracy of the system, this study used a RMSE technique.

Table 6 : Comparison between forecasting using NN and Sugeno FIS

Months	Actual	NN	Sugeno FIS
October-09	2.57	2.561	2.861006673
September-09	2.83	2.9788	3.17880203
August-09	2.75	2.721	3.124907796
July-09	2.71	2.612	2.912325667
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March-09	7.92	7.836	7.73684342
February-09	8.6	8.931	8.431810185
January-09	9.17	9.872	9.537180603
December-08	11.06	11.013	10.64255102
November-08	11.68	11.744	11.34439996
October-08	11.77	11.822	11.34444461
September-08	12.14	12.38	11.84610901
August-08	11.85	11.87	11.47310678
July-08	11.9	11.833	11.73333271
June-08	11.03	10.954	10.85488396
May-08	10.38	10.145	10.44563151
April-08	8.96	8.9	8.990007758
March-08	8.17	8.176	8.276993486
RMSE		0.203961692	0.269437532

The RMSE (Root Mean Square Error) is the squared average from differences between the estimated values with the observed values of a variable [17]. The smaller the RMSE value is, the more accurate are the forecast models. The RMSE technique is shown in Equation (18) where N, Y_t^s, Y_t^a are the amount of observations, the estimated value of the model, and the value of the observation model [17]. This technique was chosen because it was easy to implement and had been used in several previous studies such as the research conducted by Stock and Watson (1999) [11].

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^s - Y_n^a)^2} \quad (18)$$

The accuracy of the system was tested by calculating the error value with RMSE analysis techniques. In the proposed method and comparison method, each produced RMSE values. Based on Table 6, the test results of the Sugeno FIS comparison method had an RMSE value of 0.269. The proposed Neural Network method had an RMSE value of 0.204.

The smaller the error value generated is, the more accurate are the results of inflation rate forecasting. Based on the obtained RMSE values, the proposed method had a smaller value as compared to the comparison method. In other words, the Neural Network has a superior performance and better forecasting compared with the Sugeno FIS method.

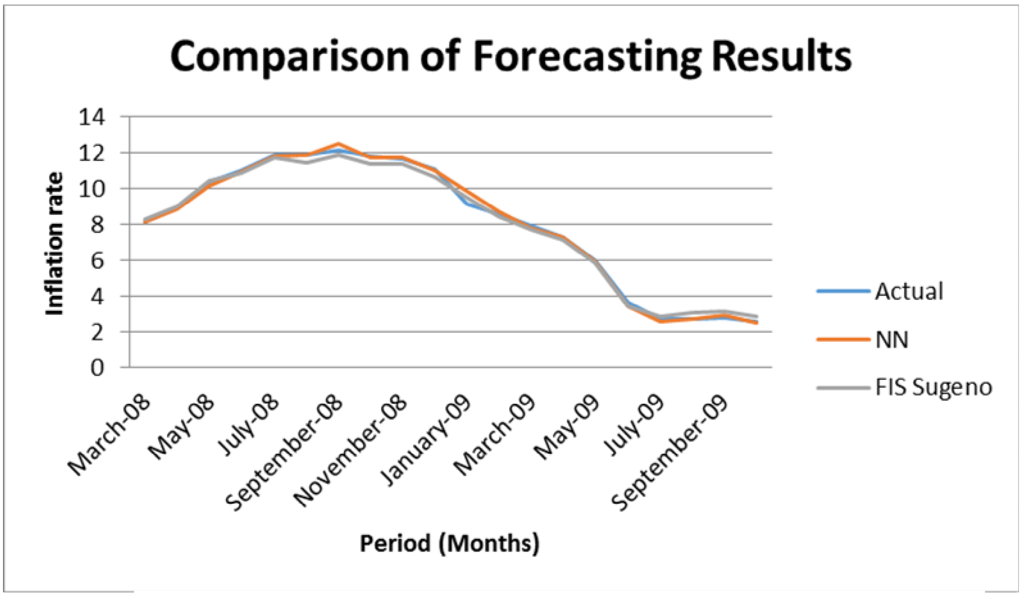

Fig. 8: Forecasting result comparison graph between Neural Network and Sugeno FIS

8 Conclusion

Various issues related to inflation rate forecasting in Indonesia have been discussed in this study. The proposed method produced better forecasting by testing the appropriate learning rate in the data learning or training process. Neural network showed superior performance with minimal errors as compared with the comparison method. The error value generated by the Neural Network is 0.204.

This study still needs to be improved, because there are many things to be tested in this study. The next study should make improvements by testing epochs, the number of hidden layers, and the number of hidden neurons to improve the accuracy of the system. For that, a method that is more powerful and efficient is needed. The method proposed for next study is the combination of Sugeno FIS with Neural Network (FNS).

References

[1] Soediyono Reksoprayitno, *Makro's Economic*, Millenium., vol. 218. Yogyakarta: BPFE-Yogyakarta, 2000.

[2] A. Tripena, "Forecasting the Consumer Price Index and Inflation in Indonesia with Box - Jenkins ARIMA method," *MAGISTRA*, vol. 23, no. 75, hal. 11, 2011.

[3] X. Xie, L. Lin, dan S. Zhong, "Process Takagi–Sugeno model: A novel approach for handling continuous input and output functions and its application to time series prediction," *Knowl.-Based Syst.*, vol. 63, hal. 46–58, Jun 2014.

[4] L. Zhang dan J. Li, "Inflation Forecasting Using Support Vector Regression," 2012, hal. 136–140.

[5] G. Moser, F. Rumler, dan J. Scharler, "Forecasting Austrian inflation," *Elsevier*, vol. 24, no. 3, hal. 470–480, 2007.

[6] I.-C. Baciu, "Stochastic Models for Forecasting Inflation Rate. Empirical Evidence from Romania," *Procedia Econ. Finance*, vol. 20, hal. 44–52, 2015.

[7] C. Hurtado, J. Luis, C. Fregoso, dan J. Hector, "Forecasting Mexican inflation using neural networks," in *Electronics, Communications and Computing (CONIELECOMP), 2013 International Conference on*, 2013, hal. 32–35.

[8] A. P. Wibawa, R. Soelaiman, dan U. N. Malang, "Effectiveness Analysis Method of Hybrid Neural Networks and Fuzzy Logic for Forecasting Foreign Exchange," 2007.

[9] D.-W. Chen dan J.-P. Zhang, "Time series prediction based on ensemble ANFIS," in *Machine Learning and Cybernetics, 2005. Proceedings of 2005 International Conference on*, 2005, vol. 6, hal. 3552–3556.

[10] S. Sadimon dan H. Haron, "Neural Network Model for Prediction of Facial Caricature Landmark Configuration using Modified Procrustes Superimposition Method.," *Int. J. Adv. Soft Comput. Its Appl.*, vol. 7, no. 3, 2015.

[11]J. H. Stock dan M. W. Watson, “Forecasting Infation,” *Elsevier*, vol. 44, hal. 293–335.

[12]E. S. Puspita dan L. Yulianti, “Weather Forecast System Design Based Fuzzy Logic,” *Media Infotama*, vol. 12, no. 1, 2016.

[13]P. E. Somaratna, S. Arunatilaka, dan L. Premarathna, “Which is better for inflation forecasting? Neural networks or data mining,” in *Information Society (i-Society), 2010 International Conference on*, 2010, hal. 116–121.

[14]K. K. Kuok, S. Harun, dan C. P. Chan, “Hourly runoff forecast at different lead-time for a small watershed using artificial neural networks,” *Int J Adv. Soft Comput Appl*, vol. 3, no. 1, hal. 68–86, 2011.

[15]“Data - The Central Bank of Indonesia.” [Daring]. Tersedia pada: http://www.bi.go.id/en/moneter/inflasi/data/Default.aspx. [Diakses: 22-Okt-2015].

[16]R. Ibarra, “Do disaggregated CPI data improve the accuracy of inflation forecasts?,” *Econ. Model.*, vol. 29, no. 4, hal. 1305–1313, Jul 2012.

[17]N. C. Long dan P. Meesad, “Meta-heuristic algorithms applied to the optimization of type-1 and type 2 TSK fuzzy logic systems for sea water level prediction,” in *Computational Intelligence & Applications (IWCIA), 2013 IEEE Sixth International Workshop on*, 2013, hal. 69–74.

[18]J. Rezaei dan R. Ortt, “Supplier segmentation using fuzzy logic,” *Ind. Mark. Manag.*, vol. 42, no. 4, hal. 507–517, Mei 2013.

[19]N. R. Sari dan W. F. Mahmudy, “Tsukamoto Fuzzy Inference System to Determine The Feasibility of Prospective Employees,” *SESINDO 2015*, 2015.

[20]A. Esfahanipour dan P. Mardani, “An ANFIS model for stock price prediction: The case of Tehran stock exchange,” in *Innovations in Intelligent Systems and Applications (INISTA), 2011 International Symposium on*, 2011, hal. 44–49.

[21]S. G. Colaco, A. M. Colaco, C. P. Kurian, dan V. I. George, “An Adaptive predictive framework to online prediction of interior daylight illuminance,” in *Advances in Energy Conversion Technologies (ICAECT), 2014 International Conference on*, 2014, hal. 174–180.