The Effectiveness of Hybrid Backpropagation Neural Network Model and TSK Fuzzy Inference System for Inflation Forecasting

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Abstract**—Forecasting may predict the accurate future condition based on the previous circumstance. Problems that may occur are related to forecasting accuracy. This study proposes a combination of two methods: Neural Network (NN) and Fuzzy Inference System (FIS) to accuratelly forecast the inflation rate in Indonesia. Historical data and four external factors were used as system parameters. The external factors in this study were divided into two fuzzy sets. While time series variables were divided into three fuzzy sets. The combination of them generated a lot of fuzzy rules that may reduce the forecasting effectiveness. As a consequence, the less fit fuzzy rules formation would produce a low accuracy. Therefore, grouping all input variables into positive parameters and negative parameters are necessary for efficiency improvement. To evaluate the forecasting results, Root Means Square Error (RMSE) analytical technique was used. Fuzzy Inference System Sugeno was used as the base line. The results showed that the combination of the proposed method has better performance (RMSE=2.154901) than its base line.**

Index Terms**—Forecasting; Inflation Rate; Neural Network (NN); Fuzzy Inference System (FIS).**

I. INTRODUCTION

Forecasting is an activity to predict the condition that might occur in the future based on the past and current information [1]. Forecasting can be a basis in creating a plan. Various methods have been used to forecast a problem by applying artificial intelligent. In forecasting, a problem that often arises is how to forecast an event with minimum errors as possible. Basically, forecasting does not necessarily give correct answers,, but it tries to provide closer to the correct answer and will probably occur with minimum errors as possible.

Inflation is one of the problems that often become a topic of discussion among economists. Economic growth is one of the benchmark for assessing a country's economic development. Economic growth means a physical development of the production of goods and services existing in a country [2]. Inflation is the tendency of rising prices of goods in general and occurs continuously [3]. Therefore, it can be concluded that inflation can be used as an indicator to assess the development of a country.

Inflation can occur due to a high consumption pattern of society. For example, a high employment opportunity creates a high level of income and further raises expenditures that exceed the economic capacity of issuing goods and services. Therefore, the consumption patterns of the society will increase. Moreover, inflation can also occur due to the rising prices of imports from the region of origin. The lower the degree of competition owned by imported goods to the domestic products, the greater the impact of changes in the price of imported goods to the inflation. Inflation is often experienced by developing countries, such as Indonesia. Indonesia's economy will decline if inflation is not controlled properly. One of the problems caused by inflation is the continuous currency debasement. Indirectly, currency debasement affects the global trading activities. The cost of daily necessities will increase and unemployment will exist everywhere.

One of the ways to control the inflation rate in Indonesia is to perform an inflation rate forecasting. It aims to provide information to the government to prepare government policy in anticipating of the inflation rate in the future. On the other hand, forecasting results can be utilized by the community at large. For the farmers, the results can be used to raise the commodity prices, since commodity is a staple item that is very important for the society. When the forecasting results indicate a high inflation rate, the farmers can raise the prices the commodity as high as possible to get profit as much as possible.

Forecasting was done based on historical data with time-series analysis technique, for example by considering the previous months where there was an increase in inflation. This study used some external factors that affect the inflation rate to determine the level of inflation. Historical data and external factors are used as input variables, while the output data is the result of forecasting. External factors used in this study include the Consumer Price Index (CPI), the interest rate (BI Rate), the money supply, and the exchange rate. These external factors have been used in several studies [4-9].

Inflation rate forecasting has been done by Moser, et al [10] and [11]. Moser, et al. who used Auto Regression Integrated Moving Average (ARIMA) for inflation rate forecasting. Further, Baciu used stochastic model to forecast the inflation rate.

Recent studies have used Backpropagation Neural Network (NN) as a method for inflation rate forecasting. Sari et al. [3]

used historical data and CPI as input variables. Accuracy obtained using Backpropagation NN method was 0.204. The accuracy technique used was the Root Mean Square Error (RMSE). Neural Network has the advantages of allowing more flexibility in terms of adaptation and having a good learning ability. Neural Network is able to detect patterns and trends in various data sets [12], but Neural Network is weak in explaining something. Therefore, it needs to be combined with fuzzy logic that has a good ability in explaining.

This study is the continuity of the previous study, which focused on forecasting inflation rate in Indonesia using time series variable and external variable, namely CPI [3]. This study proposed a combination of methods, namely the Neural Network (NN) and Fuzzy Inference System (FIS) or the so-called Neural Fuzzy System (NFS). These two methods run separately, where the data will be processed using NN first, then the output from NN will be used as input to be processed in the next stage using FIS method. NFS method has been used in several studies and one of them is the research conducted by the Wibawa and Soelaiman (2007) to forecast the foreign exchange.

II. Related Works

Several recent studies have succeeded in doing inflation rate forecasting. Zhang and Li [6] used SVR model to forecast inflation rate in China. SVR is a method used in making decisions. This method can be considered as the improvement of Linear Regression, where this method is able to generate a function with wavy results that follow the formed data path. Therefore, the result of the forecasting is more accurate than the linear regression. The system accuracy of the resulting system using the RMSE was 0.1.

Sari et al. used Backpropagation Neural Network to forecast inflation rate [3]. The study used historical data and CPI as input variables while the forecasting results represent output variable. To determine the system accuracy, Sari et al. used RMSE technique analysis. System accuracy obtained by using Backpropagation Neural Network was 0.204. Neural Network has a good learning ability, but this model has a shortcoming in explaining things.

In terms of forecasting, fuzzy logic has been successfully implemented in a wide range of issues related to forecasting using time-series data [13]. NFS has been used by [14] for nonlinear system modelling. Meanwhile, Wibawa and Soelaiman [12] used a combination of fuzzy logic and learning technique of Neural Network for forecasting the foreign exchange. The level of accuracy generated by using Mean Square Error (MSE) technique was 0.201.

III. Data Set

This study used the data set in the form of historical data from Bank Indonesia [15] and Centre for Statistics (*Badan Pusat Statistik)* [16]. The data record used comprised 99 of data ranging from October 2005 – Desember 2014.

The parameters used in this study include historical data with time-series analysis (b-1, b-2, b-3). Parameter b-1 represents a month before, b-2 represents two months before, and b-3 represents the three months before. The study also used several external factors that affect the inflation rate, including the Consumer Price Index (CPI), interest rate (BI Rate), money supply, and exchange rate. These parameters were used as input variables in the inflation rate forecasting. Meanwhile, the output variable was in the form of the inflation rate forecasting result in Indonesia. Table 1 and 2 show the examples of data record for each parameter.

Table 1
Example of Time Series Variable

Month	Actual Data	*b-1*	*b-2*	*b-3*
Dec – 13	8.38	8.37	8.32	8.4
Nov - 13	8.37	8.32	8.4	8.79
…	…	…	…	…
Oct – 05	17.89	18.38	17.11	17.03

Table 2
Example of External Variable

Month	CPI	*BI rate*	*Money Supply*	*Exchange Rate*
Dec – 13	146.84	7.50	870455	11977
Nov - 13	146.04	7.25	856146	11234
…	…	…	…	…
Oct – 05	135.15	12.25	286715	10090

To minimize the fuzzy rules, this study classified all input variables into two groups, namely positive parameter and negative parameter. The grouping is based on data linearity. An example is when the CPI rises, the inflation rate will also raise, these variables are classified into positive parameters. An example of variable classified as negative parameter is when interest rate goes down, the inflation tends to rise. Table 3 shows a classification of positive parameters and negative parameters.

Table 3
Classification of Positive and Negative Parameters

Parameter	
Positive	Negative
b-1 (past one month)	BI Rate
b-2 (past two months)	Exchange Rate
b-3 (past three months)	
CPI (Consumer Price Index)	
Money Supply	

IV. Neural Fuzzy System (NFS)

Fuzzy Neural System (NFS) is a combination of Neural Network (NN) and Fuzzy Inference System (FIS), but they are run separately. Thus, this model consists of two stages: The first stage use NN to process data to generate output, while the second stage uses FIS to process the generated output from the first stage as input variables to generate the final output in the form of forecasting [12]. In the first stage of data processing that uses NN, there are two processes, namely the training data and testing data [17], which will be described clearly in Part V. While in the second stage, the fuzzy process was done with several stages, namely fuzzification, fuzzy inference engine, and defuzzification [18]. The following section describes the NFS processes as shown in Figure 1.

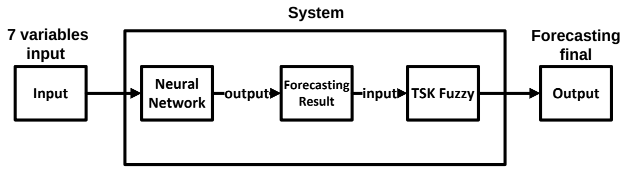

Figure 1: Workflow of NFS method

V. Data Processing on The First Stage Using Neural Network (NN)

Neural Network is an artificial representation of the human brain that always tries to stimulate the learning process in human brain [19]. NN has the ability to analyze, forecast, and make association. NN was first introduced by McCulloh and Pitts in 1943, which concluded that the combination of some simple neurons into a neural system would increase computational capabilities. Backpropagation is the NN model used in this study. In general, NN has three layers: The input layer that is connected to the hidden layer, which in turn is connected to the output layer.

As shown in Figure 1 and Figure 2, the NN architecture consists of input layer, hidden layer and output layer. In the first stage, namely, the data processing that uses NN, there are two processes, namely the training data process and testing data. The data used in these two processes were different data. Data used for the training were 69 data records (April 2008-December 2013). While for testing data, the data used were 30 data (October 2005 - March 2008).

Data training process aims to find the appropriate weight so that the best weight is obtained and used for the data testing process. The testing includes the learning rate testing, epoch number testing, neuron's number testing. Those tests were performed on each parameter, which were the positive and negative parameters. For each parameter, data processing using NN was performed separately so that an output would be produced by each parameter.

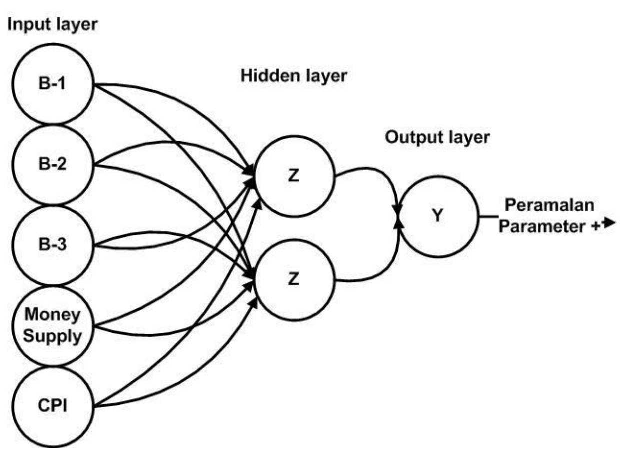

Figure 2: NN architecture with positive parameter input (three time series variables and two external variables)

Figure 2 shows the NN architecture using positive parameter as input variables. Input variables in this stage consist of three time series variables time (b-1, b-2, b-3) and two external factors (Money Supply, CPI). This process was included in the first stage, namely the data processing using Neural Network to generate an output in the form of positive parameter forecasting.

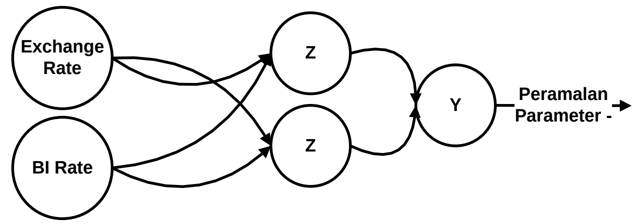

Figure 3: NN architecture with negative parameter input (two external variables)

Figure 3 is the NN architecture using negative parameter that consists of two input variables, namely the BI rate and the exchange rate. This process also includes the process in the first stage, that is the data processing using NN to generate an output in the form of negative parameter forecasting.

A. *Learning rate testing*

Learning rate testing was conducted to find the best rate learning value to be used in the next testing that is the epoch number testing. Learning rate testing performed 10 times with a range of 0 - 1. For the initial testing, the epoch number used was 2000 and the number of neurons was 3. The best learning rate was taken from the smallest average error. Table 4 and Table 5 show the results of learning rate on the positive parameter and negative parameter. For the positive parameter obtained, the best learning rate value was 0.4 with the smallest average error of 0.002274. While the best learning rate value for negative parameter was 0.9 with the smallest average error of 0.013635.

Table 4
Learning Rate Testing on Positive Parameter

Learning Rate	Epoch	Testing			Error Rate
		1	…	10	
		RMSE			
0.1	2000	0.00270	…	0.00290	0.00270
0.2	2000	0.00228	…	0.00232	0.00238
0.3	2000	0.00223	…	0.00235	0.00232
0.4	**2000**	**0.00225**	**…**	**0.00233**	**0.00227**
0.5	2000	0.00233	…	0.00230	0.00230
0.6	2000	0.00222	…	0.00243	0.00231
0.7	2000	0.00232	…	0.00233	0.00232
0.8	2000	0.00236	…	0.00204	0.00234
0.9	2000	0.00237	…	0.00239	0.00234

Table 5
Learning Rate Testing on Negative Parameter

Learning Rate	Epoch	Testing			Error Rate
		1	…	10	
		RMSE			
0.1	2000	0.01436	…	0.01436	0.01435
0.2	2000	0.01425	…	0.01420	0.01425
0.3	2000	0.01430	…	0.01437	0.01432
0.4	2000	0.01428	…	0.01429	0.01424
0.5	2000	0.01412	…	0.01386	0.01427
0.6	2000	0.01394	…	0.01426	0.01425
0.7	2000	0.01265	…	0.01307	0.01373
0.8	2000	0.01440	…	0.01427	0.01397
0.9	**2000**	**0.01231**	**…**	**0.01402**	**0.01364**

B. Epoch testing

Epoch number testing was done after the best learning rate value for each parameter (positive parameter and negative parameter) was obtained. Epoch testing performed 10 times. The best epoch number was taken from the smallest error average value. The epoch number testing was between 5000-130000 epoch. Based on the test result shown in Table 6 and Table 7, the best epoch number on positive parameter was 320000 with an error average of 0.001614. While for the negative parameter, the best epoch number was 100000 with the smallest error of 0.012533.

Table 6
Epoch Testing on Positive Parameter

Learning Rate	Epoch	Testing 1	…	10	Error Rate
		RMSE			
0.4	5000	0.00221	…	0.00194	0.00216
0.4	10000	0.00168	…	0.00173	0.00192
0.4	30000	0.00163	…	0.00159	0.00179
0.4	50000	0.00216	…	0.00167	0.00178
0.4	100000	0.00194	…	0.00161	0.00192
0.4	150000	0.00192	…	0.00192	0.00177
0.4	200000	0.00194	…	0.00167	0.00178
0.4	250000	0.00161	…	0.00192	0.00171
0.4	300000	0.00161	…	0.00160	0.00176
0.4	**320000**	**0.00160**	**…**	**0.00161**	**0.00164**

Table 7
Epoch Testing on Negative Parameter

Learning Rate	Epoch	Testing 1	…	10	Error Rate
		RMSE			
0.9	5000	0.01225	…	0.01224	0.01314
0.9	10000	0.01224	…	0.01423	0.01260
0.9	30000	0.01229	…	0.01230	0.01261
0.9	50000	0.01236	…	0.01236	0.01255
0.9	**100000**	**0.01234**	**…**	**0.01234**	**0.01253**
0.9	150000	0.01423	…	0.01227	0.01306
0.9	200000	0.01423	…	0.01423	0.01265
0.9	250000	0.01225	…	0.01225	0.01261
0.9	300000	0.01225	…	0.01423	0.01265
0.9	320000	0.01423	…	0.01225	0.01277

C. Neuron testing

Having obtained the learning rate value and the best epoch number for each parameter, the testing number of neuron was done on the hidden layer. Using the learning rate value and the best epoch number in the previous tests, the number of neuron tested was 10 times ranging from 3-10 neurons. Based on the test results in Table 8 and 9, the best epoch number for the positive parameter was 10 neurons with an average error of 0.001118 and the smallest epoch value for negative parameter was 9 neurons with an average error of 0.008074.

Table 10 summarizes of all testings based on the results of learning rate, epoch number, and neuron's number testing. The results of these testings were used to obtain the best weights of each parameter (positive and negative) to be used in the testing data stage. Weights generated during the training data are summarized in Table 11 and Table 12.

Table 8
Neuron Testing on Positive Parameter

Neuron	Epoch	Testing 1	…	10	Error Rate
		RMSE			
3	320000	0.00161	…	0.00161	0.00171
4	320000	0.00159	…	0.00188	0.00164
5	320000	0.00147	…	0.00125	0.00142
6	320000	0.00144	…	0.00120	0.00143
7	320000	0.00124	…	0.00159	0.00119
8	320000	0.00159	…	0.00135	0.00132
9	320000	0.00128	…	0.00115	0.00117
10	**320000**	**0.00093**	…	**0.00107**	**0.00112**

Table 9
Neuron Testing on Negative Parameter

Neuron	Epoch	Testing 1	…	10	Error Rate
		RMSE			
3	100000	0.0123	…	0.01234	0.012838
4	100000	0.011	…	0.01102	0.011117
5	100000	0.011	…	0.01229	0.010747
6	100000	0.0096	…	0.00878	0.010058
7	100000	0.0095	…	0.00871	0.009368
8	100000	0.009	…	0.00831	0.008829
9	**100000**	**0.007**	…	**0.00868**	**0.008074**
10	100000	0.0078	…	0.009	0.008446

Table 10
Summary of The Result of Positive and Negative Parameters

Testing Result	Parameter Positive	Negative
Learning rate	0.4	0.9
Epoch	320000	100000
Neuron	10	9

Table 11
The Weight Resulted from Positive Parameter Testing

Vij	1	2	…	9	10
1	-0.168	0.5279	…	1.1221	-0.442
2	-4.332	-1.088	…	-1.211	1.9373
3	-3.537	-0.873	…	1.3157	-1.228
4	-10.56	-1.241	…	5.2347	-3.313
5	6.7178	-10.81	…	-2.912	0.1316

Wjk	1
1	15.271
2	-18.11
3	-6.158
4	-6.321
5	-3.581
6	6.2424
7	7.3479
8	-12.3
9	8.4802
10	-4.994

Table 12
The Weight Resulted from Negative Parameter Testing

Vij	1	2	…	8	9
1	-31.761	15.195	…	-0.2468	4.4047
2	19.2111	-13.493	…	-4.4	-4.035

Wjk	1
1	3.26302
2	-8.3286
3	23.3284
4	-14.898
5	5.68693
6	-8.6902
7	-4.2008
8	-8.361
9	5.8587

D. Positive and negative parameter forecasting

Drawn from the best weight during the training data process, the testing data process was performed, where the data used was 30 of data ranging from October 2005 - March 2008. The testing data was performed on each parameter, resulting in two forecasting, namely the positive forecasting and negative forecasting. The testing data results of each parameter are shown in Table 13. These test results were used in the second stage, that is the forecasting stage using FIS.

Table 13
The Result of Positive and Negative Parameters Data Testing

Date	Actual Data	Parameter Positive	Parameter Negative
8-Mar	8.17	14.50605	7.53540
8-Feb	7.4	13.52942	7.51343
8-Jan	7.36	10.97859	7.43662
7-Dec	6.59	7.16228	7.45782
7-Nov	6.71	9.02820	6.62675
7-Oct	6.88	8.78159	7.11060
7-Sep	6.95	7.29889	8.72025
7-Aug	6.51	6.47989	7.76153
7-Jul	6.06	5.80821	6.01341
7-Jun	5.77	6.56323	7.77780
7-May	6.01	8.68317	8.36763
7-Apr	6.29	8.80595	6.79033
7-Mar	6.52	9.45659	6.16814
7-Feb	6.3	7.62608	8.68223
7-Jan	6.26	7.50961	9.93912
…	…	…	…
5-Oct	17.9	6.31516	11.79258

VI. Data Processing on The Second Stage Using Fuzzy Inference System (FIS)

Fuzzy Inference System (FIS) Sugeno is a model of fuzzy logic that is used to forecast the inflation rate in Indonesia. FIS Sugeno was developed by Takaghi, Sugeno, and Kang (TSK) [20]. FIS Sugeno was chosen for this model as it is considered suitable for time-series data such as in the study [13]. FIS Sugeno consists of three processes: Fuzzification, fuzzy inference engine, and defuzzification.

A. Fuzzification

Input variables in this study were divided into two or more fuzzy sets. Fuzzy set is a union representing a certain condition in a fuzzy variable [18]. Linguistic variables were united to fuzzy set, each of which has a membership function that has been defined [21]. Membership function is a curve showing the representation of the input data point into the membership values that have interval between 0-1. A function to determine the membership value is described by the curve. Figure 4 shows an example of a curve representing input variables b-1, b-2 and b-3 with Equation (1) and (2) [22], while Figure 5 represents the external variables.

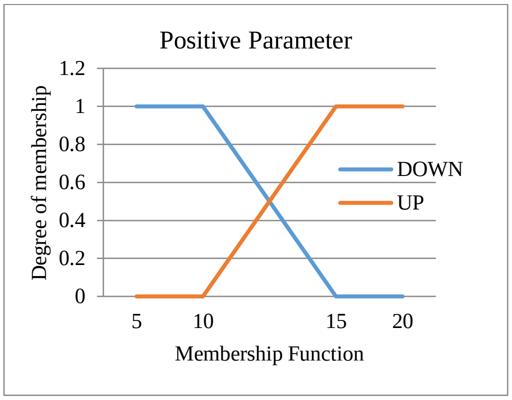

Figure 4: Positive parameter variable on each fuzzy set DOWN and UP

$$\mu\, DOWN\,(x) = \begin{cases} 1 & x \leq 10 \\ \dfrac{15-x}{5} & 10 < x < 15 \\ 0 & x \geq 15 \end{cases} \qquad (1)$$

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

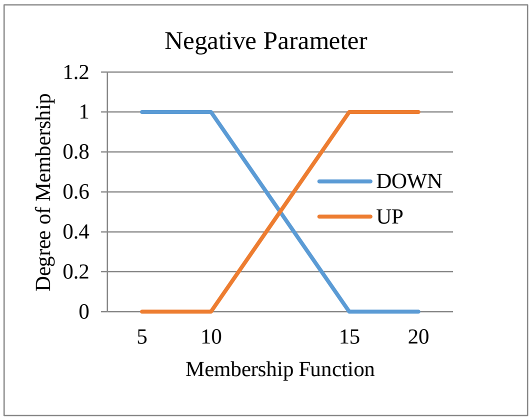

Figure 5: Negative parameter variable on each fuzzy set DOWN and UP

$$\mu\, DOWN\,(x) = \begin{cases} 1 & x \leq 10 \\ \dfrac{15-x}{5} & 10 < x < 15 \\ 0 & x \geq 15 \end{cases} \qquad (4)$$

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

B. Fuzzy Inference Engine

The results of fuzzy membership value calculation process then were inferenced to the fuzzy rules. Based on FIS Sugeno method, the implication function used was Min. Table 14 is an example of fuzzy rules used in this study. The number of fuzzy rules used in this study was 4 fuzzy rules. This amount was derived from the number of fuzzy sets (DOWN and UP) to the power of the number of fuzzy input variables (positive parameter and negative parameter). The formation of fuzzy rules in this study is more effective and efficient for data processing at the first stage using NN. All input variables were grouped into two parameters. The output of the first stage became the input variable in the second stage, thus forming two fuzzy sets.

Table 14
Fuzzy Rules

No.	Fuzzy Rules
1	IF Parameter Positif UP AND Parameter Negatif UP AND THEN z = a+b1*Parameter Positif+b2*Parameter Negatif
2	IF Parameter Positif UP AND Parameter Negatif DOWN AND THEN z = a+b1*Parameter Positif+b2*Parameter Negatif
3	IF Parameter Positif DOWN AND Parameter Negatif UP AND THEN z = a+b1*Parameter Positif+b2*Parameter Negatif
4	IF Parameter Positif DOWN AND Parameter Negatif DOWN AND THEN z = a+b1*Parameter Positif+b2*Parameter Negatif

C. Defuzzification

The output value (crisp) was obtained by transforming the input into numbers in the fuzzy sets domain or defuzzification. The results of defuzzification process were the result of the final forecasting.

VII. Result and Discussion

In this stage, data processing using FIS was performed. This process is a process in the second stage of NFS model. Data processing using FIS method in this stage aims to generate the inflation rate forecasting in Indonesia. Based on the first stage, the results of the learning rate testing, epoch number testing, and neuron's number testing are shown in Table 10. Meanwhile, Table 11 and Table 12 show the best weight generated during the training data process in the first stage. From the weight obtained, we performed testing data, which result in an output in the form of forecasting of each parameter, namely the positive parameter and negative parameter. The output was used as an input variable in the next process, namely the second stage of data processing using FIS.

The data processing using FIS is divided into three stages, namely fuzzfication, fuzzy inference engine, and defuzzification. The novelty of this study is drawn from the way to minimize the fuzzy rules so that it is more effective and efficient to generate high accuracy. This result is based on the establishment of fuzzy rules that depends on the number of fuzzy sets and the number of input variables. The input variables in this study were seven input variables with three fuzzy sets for time series variables and two fuzzy sets for external factors. Thus, in this study, all the input variables were categorized into positive parameter and negative parameter to be processed first using NN, which subsequently the obtained output produced two input variables only. The results of forecasting by using FIS Sugeno in the second stage were the results of the final forecasting NFS model, as shown in Table 15.

Table 15 presents the actual data and input variables, including the positive parameter and negative parameter, and the results of final forecasting by using NFS. Based on Table 15, the accuracy generated by using RMSE technique was 2.154901. The accuracy generated by NFS model is still better than the usual FIS Sugeno with an accuracy of 2.9418642, as shown in Table 16. Figure 6 shows the movement of forecasting results using NFS that is closer to the actual data.

Table 15
The Result of Inflation Rate Forecasting in Indonesia

Date	Actual(BI)	Positive Parameter	Negative Parameter	Forecasting NFS
8-Mar	8.17	14.506	7.535	8.995983
8-Feb	7.4	13.529	7.513	8.633435
8-Jan	7.36	10.979	7.437	7.676379
7-Dec	6.59	7.162	7.458	6.322094
7-Nov	6.71	9.028	6.627	6.507311
7-Oct	6.88	8.782	7.111	6.700447
7-Sep	6.95	7.299	8.72	7.104362
7-Aug	6.51	6.48	7.762	6.254562
7-Jul	6.06	5.808	6.013	4.997817
7-Jun	5.77	6.563	7.778	6.293572
7-May	6.01	8.683	8.368	7.395322
7-Apr	6.29	8.806	6.79	6.522538
7-Mar	6.52	9.457	6.168	6.394214
7-Feb	6.3	7.626	8.682	7.19935
7-Jan	6.26	7.51	9.939	7.888139
…	…	…	…	…
5-Oct	17.89	6.3151605	11.792578	11.43563
RMSE				2.154901

Table 16
Forecasting Result Between NFS and FIS Sugeno

Date	Actual(BI)	Forecasting	
		NFS	FIS Sugeno
8-Mar	8.17	8.995983	4.74536
8-Feb	7.4	8.633435	4.93495
8-Jan	7.36	7.676379	4.20774
7-Dec	6.59	6.322094	4.27898
7-Nov	6.71	6.507311	4.71617
7-Oct	6.88	6.700447	4.94409
7-Sep	6.95	7.104362	4.71438
7-Aug	6.51	6.254562	4.38733
7-Jul	6.06	4.997817	4.04482
7-Jun	5.77	6.293572	4.426
7-May	6.01	7.395322	4.88781
7-Apr	6.29	6.522538	5.42047
7-Mar	6.52	6.394214	5.20755
7-Feb	6.3	7.19935	5.43999
7-Jan	6.26	7.888139	6.31525
…	…	…	…
5-Oct	17.89	11.43563	18.03852
RMSE		2.154901	2.9418642

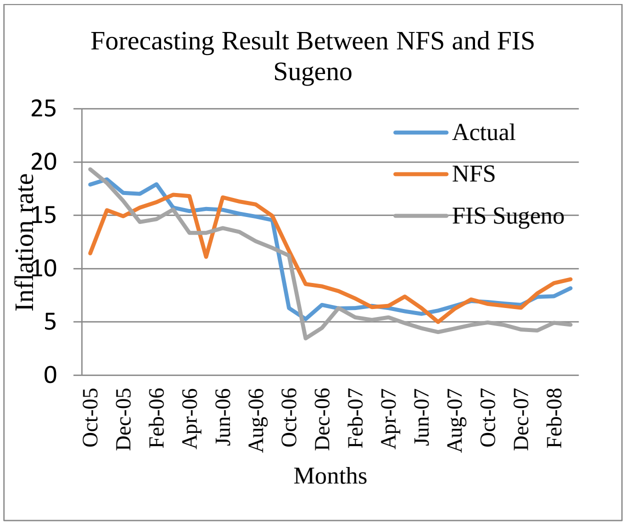

Figure 6: The Resullt of forecasting using NFS and FIS Sugeno as a comparison method

VIII. Conclusion

Neural Fuzzy System (NFS) method, proposed in this study can be implemented for the inflation rate forecasting in Indonesia. The results of RMSE calculation showed that NFS had better performance as compared to the FIS Sugeno method. With the division of input variables into positive parameter and negative parameter, it could minimize the fuzzy rules. Forecasting results using NFS method was also better than using regular FIS Sugeno with a lot of rules. The system accuracy generated by NFS using RMSE analysis technique was 2.154901.

The system accuracy resulted in this study can still be improved. One of the things that affect the system accuracy is the determination of the initial weight in the training process Neural Network. In this study, the determination of weight training was randomly determined. The determination can be less appropriate. Therefore, genetic algorithm implementation in future studies is needed to optimize the fuzzy rules and the initial weight training data process. Optimization aims to improve better system accuracy. Genetic Algorithm has been used widely to resolve issues related to the optimization, such as the study conducted by Mahmudy [25].

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