Weight Optimization of The Neural Fuzzy System (NFS) Using Genetic Algorithm for Forecasting

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***Abstract*— Inflation is a phenomenon of increasing prices on a continuous basis which results in the increase of other goods. This study proposes the Neural Fuzzy System (NFS) as a method to predict the rate of inflation in Indonesia. To improve the accuracy, the weight at this stage of Neural Network to be determined correctly. So, this research using Genetic Algorithms to determine the best weights in the training process. This weight can be used to obtained output thorough testing process. Then, it can be processed again in the next step using FIS Sugeno until obtained the end forecasting result. To increase more accurate forecasting results, the establishment of fuzzy rules must be specified correctly. It takes a novelty that minimizes the number of fuzzy rules by dividing the initial parameter into the two (positive and negative) on stage Neural Network. So, the fuzzy rules generated less. To measure the accuracy of the system used the RMSE technique. Based on this result, the proposed method obtained for 0.89.**

Keywords—inflation, forecasting, optimization Neural Fuzzy System, Root Mean Square Error (RMSE)

I. Introduction

In the world of economy, inflation can be used as an indicator to measure a country. The progress of a country depends on the level of inflation at that time. Inflation is the phenomenon of rising prices which take place continuously and it can increase the prices of other goods[1]. Inflation can come from within the country such as the increasing consumption pattern of the people. The high consumer consumption pattern of goods will cause the money supply to be out of control causing inflation. Inflation can also come from abroad. This phenomenon occurs due to the increase in imported goods. According to Dalal and Schacher[2], if the nature of imported goods is very important to *price behavior* in the importing country, then the increase in the price of imported goods will cause considerable inflationary pressures in the country.

High unemployment, an unstable economy, and slow economic growth are the effects of rising inflation. The Indonesian economy will decline if it is not controlled properly[3]. Other problems arise when inflation is not controlled properly, including the ongoing decline in currency values. Decrease in currency values due to rising prices of imported goods. The price of imported goods experiencing an increase from their origin area will affect the price of goods in the importing region, especially if the item is an important item. To control inflation, it takes a forecast for the inflation rate in Indonesia. This aims to provide information to the government to develop policies in anticipating future inflation. On the other hand, the results of forecasting can be used by the wider community. Farmers can use forecasting results to increase commodity prices when the inflation rate is high so that farmers can get large profits. In addition, forecasting results can be used as an indicator for investing. When forecasting results show a high inflation rate, then it can mean increasing investment value, especially investment in property. It can benefit investors.

Forecasting is based on historical data with *time series* analysis. *Time series* based on previous months where inflation has increased. Various studies have used historical data with time series analysis such as research conducted by Xie et al [4]. Xie at al [4] used the Sugeno FIS method with time series analysis. In addition, Xie et al [4] also use the Consumer Price Index (CPI) as an external factor that influences the inflation rate. In a forecast, it requires high accuracy because predicting various kinds of phenomenon is influenced by various factors, not just based on past experience. Therefore the selection of external factors in forecasting the inflation rate must be determined precisely because these factors will be used as a parameter to predict the inflation rate in the future.

Research that has successfully predicted the inflation rate is a study conducted by Baciu [5] and Wiyanti and Pulungan [6]. Baciu [5] uses the stochastic model to improve the inflation rate in Romania, where this model basically compares how many statistical models, including Auto-Regressive (AR), Moving Average (MA), and a combination of both. The study aims to find the best model to forecast the inflation rate. Furthermore, the ARIMA model is used by Wiyanti and Pulungan [6] to forecast the inflation rate in Indonesia. In general, the stochastic model and ARIMA have similarities, which are both based on time series analysis, where the two models have weaknesses which are unable to overcome external factors. In fact, the inflation rate is not only enough to use historical data but is influenced by various factors such as *macroeconomic factor*[7]. Fuzzy logic can be used to overcome the weaknesses of the two models. Fuzzy logic with Sugeno's Fuzzy Inference System (FIS) model can translate knowledge from experts in the form of "rules *if-then*"[8] and can solve problems related to data that has linguistic value. However, Sousa and Madrid [9] suggest that TSK *fuzzy controllers* usually have more parameters adjusted for consequent rules, so the manual settings of these parameters can be ineffective, inefficient, or sometimes impossible when there are many parameters that need to be adjusted. It can cause forecasting results to be less accurate. Therefore, a method is needed that can determine fuzzy rules appropriately. This study proposes Genetic Algorithms as an optimization method. Genetic Algorithms are chosen because the method has been used in various kinds of problems related to optimization.

In a historical data forecast or external factor data, it has an irregular or random cycle. In this case, just using fuzzy is not enough to predict the inflation rate. *Artificial Neural Network* (ANN) has the ability to predict non-linear variables[10]. ANN has good learning skills and is more adaptable to its environment. The advantage of ANN is that it can know the patterns of knowledge in various data distributions including very irregular and variable data[11], Chen and Zhang [12] state that ANN can be close to accuracy but requires a lot of data training and it is difficult to interpret the right weight so that it takes a lot of time for the data training process. To determine the right weight, this study proposes a Genetic Algorithm as a method of weight optimization in ANN. So the researchers propose the Neural Fuzzy System (NFS) method, which is the ANN method combined with fuzzy methods, where the weight on ANN will be optimized using Genetic Algorithms to improve accuracy. By minimizing fuzzy rules and optimizing the weight of the neural network, it is expected to produce a better level of accuracy in forecasting the inflation rate.

II. Related Works

In this chapter, the most recent research is related to forecasting the inflation rate using various methods. Forecasting the inflation rate has been done by several researchers, including Wiyanti and Pulungan [6], Almeida and Basturk [13], Purnama [14], Wahyuningsih et al. [15], Sari et al. [16], and Enke and Mehdiyev [17].

Wiyanti and Pulungan [6] combine the ARIMA and methods *Radial Basis Function* (RBF)to forecast the inflation rate in Indonesia. The application of the two models is based on the assumption that a single method cannot totally identify all characteristics *time series*. The results showed that the combination method had a higher accuracy compared to the ARIMA method or RBF only. The level of accuracy produced by using the proposed method is 0.2240. ARIMA is very good for short-term forecasting and for non-stationary time series data[6]. But ARIMA has disadvantages, namely for long-term forecasting, the accuracy is not good because the forecasting results will tend to be *flat* (constant / flat), so it will experience a decrease in the accuracy caused by the use of observational data in the form of non-linear *time series.* In his research, [18] stated that ARIMA is not able to model *time series* non-linear.

Almeida and Basturk [13] use fuzzy logic to predict the inflation rate of *United State* (US). The fuzzy system used is *Probabilistic Fuzzy System* (PFS) which is combined with linguistic explanations for the characteristics of the data used. Accuracy generated using the PFS method is 0.0439 which indicates that the proposed method has a good performance. Another study using *fuzzy logic* as a method is a study conducted by Purnama [14]. Purnama [14] uses the Sugeno Fuzzy Inference System to forecast the inflation rate in Indonesia based on the Consumer Price Index (CPI) data. The CPI data used in the study is divided into 7 data as input, among them are food price index, processed food price index, housing price index, clothing price index. Health price index, education price index, and transportation price index. Based on the results of the Purnama study [14], the level of accuracy produced using the Sugeno FIS method is 0.0125. Sugeno FIS has been used in several studies related to control and forecasting[19]. In addition, fuzzy systems have the advantage of being easy to apply and capable of modeling non-linear functions that are quite complex. However, to produce high accuracy it is necessary to determine fuzzy rules appropriately.

Wahyuningsih et al. [15] and Sari et al. [16] used *Artificial Neural Network* (ANN) to forecast the inflation rate. Wahyuningsih et al. [15] used monthly inflation rate data from July 1999 to 2004. In addition to inflation data, this study also uses several external factors that influence the inflation rate, including interest rates, exchange rates, and the Composite Stock Price Index (CSPI). In this research, Wahyuningsih, et al [15] used 60 data for the process *training* and 6 data for *testing*. The number of hidden layers used is two hidden layers. Based on the results of the Root Mean Square Error (RMSE) analysis, ANN provides an accuracy rate of 0.38, which means the proposed method has a better performance compared to regression analysis as a comparison method. Sari et al. [16] also used ANN as a method of forecasting the inflation rate in Indonesia. Sari et al. [16] use historical data and CPI as external factors that influence the inflation rate. In this report, Sari et al. [16] used 50 data for training data, and 20 data for testing data. The level of accuracy produced by this study is 0.628. In doing forecasting, ANN has advantages compared to conventional methods. ANN can easily adapt to its environment through good learning skills. In addition, ANN is able to detect patterns or trends in various data sets including irregular (non-linear) data by [20]. However, ANN has a weakness in determining the right weight to produce high accuracy.

Enke and Mehdiyev [17] use an Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast inflation in the US. The study uses seven input variables, namely the *Industrial Production Index*, *Producer Price Index*, M1 *Money Stock*, M2 *Money Stock*, *10-Year Treasury Constant Maturity Rate*, Japan / US *Foreign Exchange Rate*, and *Moody's Seasoned Aaa Corporate Bond Yield* to forecast inflation in the future. Data records were selected from January 2000 to January 2014. The results of data accuracy were obtained using the RMSE technique of 0.837.

Implementation of Neural Fuzzy System on Intelligent Systems to forecast foreign exchange [20]. In previous studies, the NFS method has been used by Wibawa and Soelaiman [20] In forecasting foreign exchange the *Back propagation* 5-6-13-1 Levenberg-Marquardt network produced the fastest training with 1895/30000 epoch with MSE 0.201112 and accuracy (% B) 92.06349. Forecasting results will be used as input fuzzy logic to get a decision to sell, hold or buy foreign exchange based on a one day sell strategy. The accuracy of the system made is 85.71428571%. From the results of these tests, it can be concluded that the NFS method is the right method for forecasting the inflation rate. Forecasting using the NFS method has shown several advantages, namely easy to operate and accelerate the learning process[21].

This research uses several comparative methods to predict the inflation rate in Indonesia. The comparison method used is a method that has been used in several studies related to forecasting as previously described. So, to produce high accuracy, we need a comparison that has often been used in forecasting problems. The comparison method used in this study includes the ARIMA method, FIS Sugeno, FIS Optimization Sugeno, *Back propagation*, FNS, NFS (without optimization) and ANFIS.

III. DATA SET

This research involves several data sets to predict the inflation rate in Indonesia. Historical data and external factor data are selected as parameters for forecasting inflation. Historical data uses analysis *time series*, where analysis *time series* is an important area of a forecast that uses past history which is then analyzed to develop a model that illustrates fundamental relationships[18].

TABLE I. CORRELATION ANALYSIS OF VARIABLE INPUT

		Current	b1	b2	b3
Currents	Pearson Correlation	1	.939 **	.854 **	.775 **
	Sig. (2-tailed)		0	0	0
	N	99	99	99	99
(B-1)	Pearson Correlation	.939 **	1	.938 **	.854 **
	Sig. (2-tailed)	0		0	0
	N	99	99	99	99
(B-2)	Pearson Correlation	.854 **	.938 **	1	.938 **
	Sig. (2-tailed)	0	0		0
	N	99	99	99	99
(B-3)	Pearson Correlation	.775 **	.854 **	.938 **	1
	Sig. (2-tailed)	0	0	0	
	N	99	99	99	99
**. Correlation is significant at the 0:01 level (2-tailed).					

Based on the analysis *time series*, several variables have been selected as input variables, namely *b-1* (one month ago), *b-2* (two months ago), *b-3* (three months ago). Historical data on the inflation rate in this study was obtained from the official portal *open source* Bank Indonesia October 2005 - December 2013. Based on the results of correlation analysis using SPSS, the three variables had a correlation value between -1 ≤ correlation ≤ 1 which means direct correlation or direct linear relationship between actual variables and other variables [22]. The results of the correlation analysis also state that there is a significant relationship between the actual variables and other variables with a tolerance of 1%. Table I shows the results of the correlation analysis of each variable against the inflation rate.

TABLE II. EXPOSURE TO EXTERNAL FACTORS AFFECTING INFLATION

Researcher	EV	BR	MS	CPI	BDP	TCG
Wulan and Nurfaiza, (2015)	v	V	v			
Kooths, et al (2003)				v		
Zhang and Li (2012)				v		
Arlt and Arltova (2015)				v		
Almeida and Basturk (2015)					v	
Tang and Zhou (2015)				v		v
Fitriah and Timeless (2011)	v	V				
Amrin, et al (2014)	v	V	v			

EV : Exchange Rate
BR : BI Rate
MS : Money Supply
CPI : Consumer Price Index
BDP : Bruto Domestic Product
TCG : Total of Consumer Goods Retail

In addition to historical data, the data used in the form of data of external factors that affect the rate of inflation in Indonesia. This study uses the data because there are other factors that affect the rate of inflation in addition to the time-series data[1], Several previous studies are shown in Table II have used the external factors that affect the rate of inflation. Based on Table II, been external factors that are widely used by researchers, the Consumer Price Index (CPI), the Money Supply (Money Supply), Exchange (Exchange), and the Interest Rate (BI Rate). The data obtained from the external factors official portal of open-source Indonesian Central Statistics Agency (BPS).

From the data obtained can be formed a graph showing the data according to the time pattern of development. Based on the data that has been obtained, inflation is classified as having a pattern cycle data. The data patterns are affected by long-term economic fluctuations. These cyclical patterns have a longer duration and vary from one cycle to another cycle[23], These parameters are used as input variables in this study and summarized in Table III.

In this study, these parameters are divided into two parts, namely a positive parameter and negative parameters, as shown in Table IV. The division of these parameters aims to minimize the number of rule (rule) at the stage of forecasting receipts fuzzy Sugeno FIS, determination of fuzzy rules can affect the accuracy of forecasting.

TABLE III. VARIABLE INPUT

Variable Input	
Parameter	**Information**
Time Series	*b-1* *b-2* *b-3*
External Factors	CPI (Consumer Price Index) Money Supply (Number of Money Supply) BI Rate (Interest Rate) Exchange Rate (Exchange Rate)

TABLE IV. POSITIVE AND NEGATIVE PARAMETERS

Parameter	
Positive	**Negative**
b-1 *b-2* *b-3* CPI (Consumer Price Index) Money Supply (Number of Money Supply)	BI Rate (Interest Rate) Exchange Rate (Exchange Rate)

IV. NEURAL FUZZY SYSTEM (NFS)

This study uses the Neural Fuzzy System (NFS) method, where the structure of this method is nothing but combining the Neural Network model with the Fuzzy Inference System. The Neural Network model used is *Back propagation*, while the fuzzy model used is Sugeno's Fuzzy Inference System. The NFS model mechanism is to implement *Back propagation* first to produce forecasting on each negative and positive parameter, then the forecasting result will be used as Sugeno FIS input. Where is the forecasting result of Sugeno FIS process as the final result of forecasting.

A. Artificial Neural Networks

Artificial Neural Network (ANN) is an artificial representation of the human brain that always tries to stimulate the learning process in the human brain [24]. This study uses the Neural Network as a forecasting method in the early stages. ANN has the ability to analyze, forecast, and associate. ANN was first introduced by McCulloh and Pitts in 1943 which concluded that the combination of several simple neurons into a neural system would enhance computational ability. ANN is determined by 3 things, namely (1) the pattern of relationships between neurons (network architecture); (2) methods for determining link weights (learning or training methods); and (3) activation function.

In general, ANN has 3 layers, i.e. the input layer which is connected to the hidden layer which is then connected to the output layer[25]. Because there is no specification of the number of hidden layers and neuron hidden to use, the appropriate ANN model must be found by modifying iteratively the number of neurons and hidden layers and selecting the model with the best performance (the smallest error during the learning phase).

ANN modeling process is divided into two, namely training and testing. The training process is a learning process from a neural network system that regulates input values as well as how to map them to output until the appropriate model is obtained. This process occurs when setting weights. While the testing process is a process of testing the accuracy of the models that have been obtained from the training process.

B. Fuzzy Inference System (FIS) Sugeno

Fuzzy logic is closely related to inference systems. This study uses a fuzzy inference system with the Sugeno model. Sugeno FIS is more suitable for historical data that has a pattern or cycle with time series analysis techniques[26] Reasoning with Sugeno's method has several stages, namely fuzzification, inference machines, and defuzzification. However, the output in this method is not a fuzzy set, but in the form of a linear equation[9].

C. Neural Fuzzy System

This study will use a Neural Fuzzy System (NFS) as a method. NFS is a combination of Neural Network and Fuzzy Logic. In this system, *Back propagation* Neural Network is only used at the initial stage to produce forecasting on each parameter (positive or negative). After that, the Neural Network will be stopped and only the fuzzy system will be executed, resulting in final forecasting. The NFS model is shown in Fig. 1.

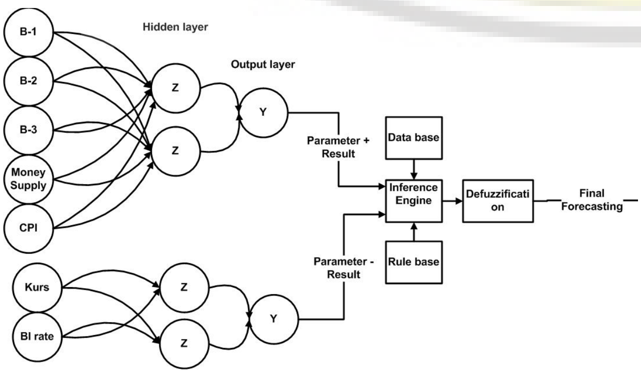

Fig. 1. A block diagram of the method of Neural Fuzzy System (NFS).

D. Optimization using GA

To find the Neural Network weights that are right for inflation rate forecasting, a search is needed. The problem is that the search can be very broad. Manually, to find the right weight on the Neural Network with extensive search is very difficult, because it will take a long time. To shorten the search time this study proposes a heuristic algorithm. The genetic algorithm is one of the heuristic algorithms that can produce better solutions and more efficient time. Genetic algorithms work by coating represents a solution in the form of chromosomes[27].

After going through several tests to determine the number of neurons that have the lowest accuracy, there are 10 neurons in the positive parameters, while for the negative parameters, 9 neurons are obtained. The chromosome design conducted based on the amount of weight to be optimized, the number of neurons in the hidden layer will be multiplied by the number of input neurons and added by multiplying the number of output neurons with the number of hidden neurons. So that we get 60 weights for positive parameters and 27 for negative parameters.

V. Numerical Example

The weight on the Neural Network must be determined precisely to produce optimal system performance, resulting in forecasting with high accuracy. For this reason, several trials are needed to find the best weight. In this study using 69 record data with 7 parameters, 5 input variables for positive parameters (b-1, b-2, b-3, CPI, Money Supply) and 2 input variables for negative parameters (Interest Rate, Exchange Rate). Data was taken from April 2008 - December 2013 (5 years)[28]. Neural Network weights are represented as chromosomes at the initialization stage. In section V it has been explained that the number of weights that will be represented as chromosomes is 60 weights for positive predictors and 27 for negative parameters. Each parameter will be searched for the best weight during the training process.

To produce the best weight, the initial test is carried out, which is to find the learning rate, where the value will be used to find the best number of epochs which are then used to find the best number of neurons. The number of these neurons can determine the amount of weight that will be used as a chromosome representation. This stage uses a simple *Back propagation* model, namely with feedforward and *Back propagation* stages. This stage is called the data training process. Table V and Table VI show the results of the learning rate testing for each parameter.

TABLE V. Result of Testing The Learning Rate on Positive Parameters

Learning Rate	Total Epoch	Trial Learning Rate			Average Error
		1	...	10	
		RMSE			
0.1	2000	0.002704	...	0.002903	0.002702
0.2	2000	0.002281	...	0.002324	0.002383
0.3	2000	0.002229	...	0.00235	0.00232
0.4	**2000**	**0.00225**	**...**	**0.002328**	**0.002274**
0.5	2000	0.002327	...	0.002298	0.002297
0.6	2000	0.002224	...	0.002431	0.002313
0.7	2000	0.00232	...	0.002327	0.002318
0.8	2000	0.002358	...	0.002043	0.002341
0.9	2000	0.00237	...	0.002387	0.00234

TABLE VI. RESULT OF TESTING THE LEARNING RATE ON NEGATIVE PARAMETERS

Learning Rate	Total Epoch	Trial Learning Rate			Average Error
		1	...	10	
		RMSE			
0.1	2000	0.01436	...	0.014363	0.015232
0.2	2000	0.014247	...	0.014202	0.012363
0.3	2000	0.014297	...	0.014366	0.016122
0.4	2000	0.014275	...	0.014292	0.012122
0.5	2000	0.014123	...	0.013857	0.012366
0.6	2000	0.013936	...	0.014263	0.013776
0.7	2000	0.012652	...	0.013065	0.012431
0.8	2000	0.014396	...	0.014273	0.012363
0.9	**2000**	**0.012305**	...	**0.014022**	**0.012213**

The learning rate trial is done with a range of 0-1. In the initial test epoch, 2000 was used and the number of neurons 3 was to accelerate computation time. However, the number of epochs and the number of neurons will still be tested. The number of epochs to be tested starts from 5000-320000. While the number of neurons starts from 3-10 neurons. Based on the learning rate test the value of 0.4 with RMSE is 0.002274 for positive parameters. While the negative parameters of the selected learning rate value are 0.9 with RMSE of 0.0122. This value can be used to find the best epoch based on the smallest RMSE value. Table VII and Table VIII show the results of the epoch test on each parameter.

Based on the smallest average error values shown in Table VII, the number of selected epochs is 320000 epoch with RMSE of 0.001641136 for positive parameters. While the smallest average value shown in Table VIII shows the number of epochs of 100000 with RMSE 0.012533 for negative parameters. The number of epochs is used to test the best number of neurons in the following tests.

TABLE VII. RESULT OF TESTING EPOCH ON POSITIVE PARAMETERS

Learning Rate	Total Epoch	Trial Learning Rate			Average Error
		1	...	10	
		RMSE			
0.4	5000	0.00221	...	0.001935	0.002156058
0.4	10000	0.001682	...	0.001734	0.00191565
0.4	30000	0.001627	...	0.00159	0.001789981
0.4	50000	0.002163	...	0.001672	0.001782679
0.4	100000	0.001938	...	0.001612	0.001916099
0.4	150000	0.001924	...	0.001922	0.001769876
0.4	200000	0.001936	...	0.001674	0.001775525
0.4	250000	0.001614	...	0.00192	0.001709769
0.4	300000	0.001614	...	0.001601	0.00176397
0.4	**320000**	**0.001602**	...	**0.001614**	**0.001641136**

TABLE VIII. RESULT OF TESTING EPOCH ON NEGATIVE PARAMETERS

Learning Rate	Total Epoch	Trial Learning Rate			Average Error
		1	...	10	
		RMSE			
0.9	5000	0.012249	...	0.012235	0.013135
0.9	10000	0.012239	...	0.01423	0.012602
0.9	30000	0.012292	...	0.012303	0.012611
0.9	50000	0.012362	...	0.012363	0.012546
0.9	**100000**	**0.012343**	...	**0.012343**	**0.012533**
0.9	150000	0.01423	...	0.012271	0.013061
0.9	200000	0.01423	...	0.01423	0.012651
0.9	250000	0.012253	...	0.012253	0.012613
0.9	300000	0.012252	...	0.01423	0.012647
0.9	320000	0.01423	...	0.012252	0.012774

Based on the results of testing the number of neurons shown in Table IX, the number of 10 neurons was chosen as the number of the best neurons with RMSE of 0.0011176 for positive parameters. Whereas in the negative parameter the number of neurons 9 with the smallest RMSES is 0.0080737 The number of selected neurons can be used for testing using Genetic Algorithms.

TABLE IX. RESULT OF NEURON TESTING IN POSITIVE PARAMETERS

Total Neurons	Learning Rate	Epoch	Many Experiments			Average Error
			1	...	10	
			RMSE			
3	0.4	320000	0.00161425	...	0.001614	0.0017045
4	0.4	320000	0.00159131	...	0.001884	0.0016377
5	0.4	320000	0.001471	...	0.00125	0.0014157
6	0.4	320000	0.00144249	...	0.001202	0.0014331
7	0.4	320000	0.0012441	...	0.001588	0.0011937
8	0.4	320000	0.00158764	...	0.001354	0.0013232
9	0.4	320000	0.00127768	...	0.001151	0.0011716
10	**0.4**	**320000**	**0.00093127**	...	**0.001071**	**0.0011176**

TABLE X. RESULT OF NEURON TESTING IN NEGATIVE PARAMETERS

Total Neurons	Learning Rate	Epoch	Many Experiments			Average Error
			1	...	10	
			RMSE			
3	0.9	100000	0.012339	...	0.012341	0.0128378
4	0.9	100000	0.011016	...	0.011016	0.011117
5	0.9	100000	0.011019	...	0.01229	0.0107471
6	0.9	100000	0.009603	...	0.008778	0.0100584
7	0.9	100000	0.00945	...	0.00871	0.009368
8	0.9	100000	0.009001	...	0.008307	0.0088295
9	**0.9**	**100000**	**0.007012**	...	**0.008679**	**0.0080737**
10	0.9	100000	0.007767	...	0.009002	0.008446

The next test is testing the determination of the population (PopSize), mr (mutation rate), and cr (crossover rate). PopSize testing is done to get the best PopSize with the greatest fitness value. This test is carried out in the range of 20 - 1000. While the tests of mr and cr are carried out with a combination of values between 0 - 1 as shown in Table XII. Table XI shows the results of the PopSize test. Tests for PopSize, mr, and cr are performed on each parameter (positive and negative).

TABLE XI. RESULT OF THE POPULATION TESTING IN POSITIVE PARAMETERS

Total Population	Total Individual	Cr	Mr	Experiment To -			Average Fitness
				1	...	10	
				Fitness			
10	100	0.5	0.5	12.602534	...	105.95241	149.91993
25	100	0.5	0.5	140.69325	...	129.34246	181.06451
50	100	0.5	0.5	485.30427	...	28.382544	143.62335
100	100	0.5	0.5	1183.4152	...	37.686157	172.30216
200	100	0.5	0.5	89.667858	...	35.942732	156.12599
500	**100**	**0.5**	**0.5**	**748.64931**	...	**307.33135**	**260.96306**
1000	100	0.5	0.5	40.863767	...	20.99254	161.60438

TABLE XII. RESULT OF THE POPULATION TESTING IN NEGATIVE PARAMETERS

Total Population	Total Individual	Cr	Mr	Experiment To -			Average Fitness
				1	...	10	
				Fitness			
10	100	0.5	0.5	110 127	...	40.14691	191.1774
25	100	0.5	0.5	258.8229	...	39.23113	79.83403
50	100	0.5	0.5	478.4883	...	29.82918	261.8555
100	100	0.5	0.5	137.0958	...	184.4376	156.1266
200	100	0.5	0.5	38.41651	...	70.17301	81.49279
500	100	0.5	0.5	69.98642	...	1302.606	212.3139
1000	**100**	**0.5**	**0.5**	**650.3466**	...	**104.8657**	**264.2794**

The PopSize test on positive parameters (Table XI) is done with the initial number of individuals 100 and the initial value cr = 0.5 mr = 0.5. Based on the testing of the PopSize amount, the PopSize amount is 500. The number of PopSize is chosen because it has the largest fitness value of 260.96306.

While in the negative parameter, the number of PopSize selected is 1000. The number of PopSize has the largest fitness value, 264.2794 as shown in Table XII. The selected PopSize number is used for testing the following cr and mr.

TABLE XIII. RESULT OF CR MR TESTING ON PARAMETER POSITIVE

Total Population	Total Individual	Cr	Mr	Experiment To -			Average Fitness
				1	...	10	
				Fitness			
500	100	0.1	0.9	181.50173	...	43.692034	144.94293
500	100	0.2	0.8	93.158332	...	47.824271	94.176707
500	100	0.3	0.7	304.81213	...	496.72802	184.53536
500	100	0.4	0.6	45.82206	...	60.528358	188.3514
500	100	0.5	0.5	14.342482	...	42.691972	203.26011
500	100	**0.6**	**0.4**	**26.148935**	...	**56.477556**	**377.6552**
500	100	0.7	0.3	1653.9233	**...**	120.87404	230.65588
500	100	0.8	0.2	106.41545		18.472976	153.05628
500	100	0.9	0.1	24.452781		1671.3534	288.45946

TABLE XIV. RESULT OF CR MR TESTING ON NEGATIVE PARAMETERS

Total Population	Total Individual	Cr	Mr	Experiment To -			Average Fitness
				1	...	10	
				Fitness			
1000	100	0.1	0.9	315.6562	...	686.5175	737.7783
1000	100	**0.2**	**0.8**	**7320.154**	...	**410.2021**	**12130.31**
1000	100	0.3	0.7	732.6069	...	220.0882	2091.223
1000	100	0.4	0.6	189.9886	...	244.3114	620.2795
1000	100	0.5	0.5	2659.945	...	380.7099	908.3226
1000	100	0.6	0.4	232.2159	...	703.0903	985.2067
1000	100	0.7	0.3	301 096	**...**	152.9327	1718.582
1000	100	0.8	0.2	324.4617		1391.198	3672.194
1000	100	0.9	0.1	268.0211		1207.333	694.8061

The last test is to test the value of cr and mr, which is used to determine the best value of cr and mr so as to produce an optimal solution. The value of cr and mr used in this test considers the value of cr and mr in each test scenario with an amount equal to 1, because the test carried out must be fair. So the number of offspring produced in each test scenario must have the same number [29]. Tests of cr and mr on positive parameters obtained values of cr = 0.6 and mr = 0.4. This value is the best value based on the largest fitness value, namely 12130.31 shown in Table XIII. While the best cr and mr values obtained by negative parameters are cr = 0.2 and mr = 0.8. the value is obtained from the largest fitness value shown in Table XIV. Based on the results of the testing above it can be concluded that the results of the training process with the number of neurons 10, the number of PopSize 500, cr = 0.6 mr = 0.4 in the positive parameters have produced weights, where the weight can be used in the next stage, namely testing data (testing data) . As with positive parameters, negative parameters also produce weights during the training process using the number of neurons 9, the number of PopSize 1000, cr = 0.2 mr = 0.8. The results of these tests can be summarized in Table XV.

TABLE XV. SUMMARY OF TEST RESULTS

Examination	Parameter +	Parameters -
the number of neurons	10	9
Total PopSize	500	1000
cr	0.6	0.2
mr	0.4	0.8

VI. RESULT AND DISCUSSION

At this stage, data testing (data testing) is carried out, which is the final stage of the *Back propagation* Neural Network. Data testing is done using the feedforward process only, without using the *Back propagation* stage. The final result of this stage is forecasting. This stage uses data as much as 30 data records from October 2005 - March 2008. Testing data is done after the results obtained from the previous tests in section VI. In section VI several tests have been carried out to obtain the best weight for each parameter. These weights are shown in Table XVI and Table XVII. Each table represents the *Vij* weight where the weight is the weight of the *i*-input neuron leading to the *j*-hidden neuron. while the *Wjk* weight represents the weight of the *j*-hidden neuron leading to the output neuron k.

TABLE XVI. FINAL WEIGHT TEST RESULTS IN POSITIVE PARAMETER

Vij	1	...	10
1	-0168	...	-0442
2	-4332	...	1.9373
3	-3537	...	-1228
4	-10.56	...	-3313
5	6.7178	...	0.1316

Wjk	1
1	15 271
2	-18.11
3	-6158
4	-6321
5	-3581
6	6.2424
7	7.3479
8	-12.3
9	8.4802
10	-4994

TABLE XVII. FINAL WEIGHT TEST RESULTS IN NEGATIVE PARAMETER

Vij	1	...	9
1	-31 761	...	4.4047
2	19.2111	...	-4035

Wjk	1
1	3.26302
2	-8.3286
3	23.3284
4	-14 898
5	5.68693
6	-8.6902
7	-4.2008
8	-8361
9	5.8587

Through the process of testing data, forecasting for each parameter is produced (Positive and Negative). Forecasting is generated using the best weights shown in Table XVI and Table XVII. The forecasting results are shown in Table XVIII. Forecasting results at this stage are used as input variables in the next stage, namely forecasting using Sugeno Fuzzy Inference System (FIS).

TABLE XVIII. THE RESULTS OF POSITIVE PARAMETERS AND PARAMETER FORECASTING NEGATIVE

Date	Actual	Parameter Positive	Parameter Negative
Mar-08	8.17	14.506	7.535
Feb-08	7.4	13.529	7.513
Jan-08	7.36	10.979	7.437
Dec-07	6.59	7.162	7.458
Nov-07	6.71	9.028	6.627
Oct-07	6.88	8.782	7.111
...	...	...	...
Oct-05	17.89	6.31516046	11.79257785

At the forecasting stage using Sugeno FIS, the formation of fuzzy set boundaries and fuzzy rules must be determined correctly. In the previous stage, namely forecasting using the Neural Network method, the parameters or input variables are divided into two, namely positive parameters and negative parameters. This aims to minimize the number of fuzzy rules in the forecasting stage using Sugeno FIS because it is very difficult to form fuzzy rules if there are too many input variables and must be adjusted to the number of fuzzy sets. So we need to share parameters. At this stage, 4 fuzzy rules are used as shown in Table XIX. This value is obtained from the number of fuzzy sets of the number of input variables[8]. While the fuzzy set used in each input variable is 2 fuzzy sets namely HIGH and LOW[8].

TABLE XIX. FUZZY RULES

Rn	Rules
R1	IF Positive HIGH AND Negative HIGH THEN Z = a + b1.Positive + b2.Negative
R2	IF Positive HIGH AND Negative LOW THEN Z = a + b1.Positive + b2.Negative
R3	IF Positive LOW AND Negative HIGH THEN Z = a + b1.Positive + b2.Negative
R4	IF Positive LOW AND Negative LOW THEN Z = a + b1.Positive + b2.Negative

Based on the input variables used in the Sugeno FIS process, the formation of fuzzy membership limits and fuzzy sets on input "positive parameters" are divided into two fuzzy sets LOW domain [4-14] and HIGH [9-19], showed in Equation (1) and (2). While the "negative parameters" f the fuzzy set is divided into two fuzzy sets, namely LOW [5-14] and HIGH [10-19]. After going through the above processes, the next process is defuzzification, where this process is a process of re-mapping fuzzy values into crisp numbers which are the solution to the problem[8]. The process of defuzzification results in final forecasting of the inflation rate as shown in Table XX.

$$\mu\, LOW\,(x) = \begin{cases} 1 & x \le 9 \\ \frac{14-x}{5} & (9 < x < 14) \\ 0 & x \ge 14 \end{cases} \qquad (1)$$

$$\mu\, HIGH\,(x) = \begin{cases} 0 & x \le 9 \\ \frac{x-9}{5} & (9 < x < 14) \\ 1 & x \ge 14 \end{cases} \qquad (2)$$

TABLE XX. FINAL FORECASTING RESULTS USING ONFS

date	Currents	Parameter Positive	Parameter Negative	Forecasting ONFS
Mar-08	8.17	14 506	7,535	8.995983
FEB-08	7.4	13 529	7513	8.633435
Jan-08	7.36	10 979	7437	7.676379
Dec-07	6.59	7162	7,458	6.322094
Nov-07	6.71	9028	6627	6.507311
Oct-07	6.88	8782	7,111	6.700447
Sep-07	6.95	7299	8.72	7.104362
Aug-07	6.51	6:48	7762	6.254562
Jul-07	6.06	5808	6013	4.997817
Jun-07	5.77	6563	7778	6.293572
May-07	6.01	8683	8368	7.395322
APR-07	6.29	8806	6.79	6.522538
Mar-07	6.52	9457	6168	6.394214
FEB-07	6.3	7626	8,682	7.19935
Jan-07	6.26	7:51	9939	7.888139
...	...	...	...	...
Oct-05	11.00	10310.00	17.89	11.984353
RMSE				0.8913624
TIME				15 sec

Table XX shows a comparison between the results of the forecast using the ONFS proposed method and the actual data. Fig. 6 shows that forecasting results show performance that is quite good at approaching actual data. To measure the accuracy of the system, this study uses the Root Mean Square Error (RMSE) technique. It was chosen because this method has been used successfully by several previous studies related to forecasting cases, such as Santika et al. [30] and Dawan et al. [31]. RMSE is the root of the estimated value minus the observation value. The smaller the RMSE value, the more accurate the proposed model. The RMSE equation is shown in Equation 3, whereas T is the number of data, s is the actual data, a is the result of observation.

$$RMSE = \sqrt{\frac{1}{T}\sum (Y_t^s - Y_t^a)^2} \qquad (3)$$

System accuracy is tested by counting errors or RMSE. The results of testing the ONFS method using the RMSE technique of 0.8913624. Based on these results, GA proves that GA can produce the best weights during the data training process. Where, this weight is used as the best weight in the data testing process. The best weight is chosen based on the best fitness value that has been through the process of testing the number of epoch, individual, and cr mr testing. Several methods were also used in this study as a comparison method, including FIS Sugeno, FIS Optimization Sugeno, *Back propagation*, ANFIS, ARIMA, FNS, and NFS (without optimization). The accuracy produced by each comparison method will be compared with the proposed method (ONFS). Table XXI shows a comparison between the ONFS method and the comparison method.

TABLE XXI. COMPARISON OF METHODS ONFS THE COMPARISON METHOD

Comparison	
Method	**RMSE**
FIS Sugeno	3.536
Optimization FIS Sugeno	1.219
Back propagation	4.261
ANFIS	7.717
FNS	2.268
NFS	2.155
NFS optimization (ONFS)	**0.891**

Based on the results of testing several comparison methods, ONFS is still superior to the comparison method with the smallest RMSE value of 0.8913624. This shows that the system performance generated using the ONFS method is more optimal compared to other comparative methods such as Sugeno FIS, Sugeno FIS Optimization, *Back propagation*, ARIMA, ANFIS, FNS, and NFS (without optimization).

VII. CONCLUSION

Problems related to forecasting the inflation rate in Indonesia have been discussed in this paper. The combination between Neural Network optimized and Sugeno FIS produces better results by applying tests in the previous stage, namely testing learning rate values, number of epochs, number of neurons, number of PopSize and combinations of crossover rate (cr) and mutation rate (mr) . ONFS shows better performance with a minimum error compared to comparison methods. The error value generated using the RMSE technique is 0.8913624

This research still needs improvement, because the resulting error value can still be improved. Because the smaller the error value produced, the more accurate the forecast is produced. For further research, testing of the number of hidden layers of Neural Network and optimization of membership functions in Sugeno FIS can be obtained so that the number of hidden layers and the best membership functions can improve the accuracy of the current system.

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