Improving Adaptive Learning Rate With Backpropogation on Retail Rice Price Prediction in Traditional Markets

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Abstract

Rice is the most important staple food and carbohydrate food in the world especially people in Indonesia. This study aims to predict the retail price of rice in traditional markets using backpropogation by improvising Adaptive Learning Rate to increase the value of accuracy. Data sources were obtained from the Central Statistics Agency (BPS) in 33 provinces in Indonesia for the retail price of rice in the traditional market (Rupiah / kg) for the past 6 years (2011-2016). The results of the study state that the improvised learning rate uses 2 models: 2-10-1 and 2-15-1 (LR= 0,1; 0,5; 0,9) that the best architectural models are 4-15-1 (LR= 0.9) with an accuracy of 82%, Training MSE 0,000999936, Testing MSE 0.016051433 and Epoch 20515. The results of this study are expected to provide input to the government in providing input on predictions of retail rice prices that have an impact on the stability of rice prices in Indonesia.

Keywords: *Learning rate, Improvisation, Prediction, Rice Prices, Backpropogation.*

1. Introduction

Rice is a food source of carbohydrates and the most important staple food in the world. This is true in Asia where rice is the staple food for the majority of the population and is home to farmers who produce around 90% of total world rice production. For the people of Indonesia consuming rice is a basic need so that Indonesia is recorded as the country with the highest rice consumption in the world. Based on FAOSTAT December 2014 data sources, the country of Indonesia is one of the countries in Asia as the largest rice producing country in the world.

Table 1. The Largest Rice Producer in Asia

Country	Production Volume
China	208,100,000
India	155,500,000
Indonesia	70,600,000
Bangladesh	52,400,000
Vietnamese	44,900,000
World	**741,500,000**

Even though Indonesia is one of the biggest rice producing countries in the world, Indonesia still needs to import rice almost every year. This situation is caused by farmers using sub-optimal farming techniques coupled with large per capita rice consumption. Indonesia is also one of the largest per capita rice consumption in the entire world where Indonesians spend more than half of their total expenditure on food ingredients. Therefore the government must regulate the distribution process and maintain the stability of rice prices in Indonesia. Based on the above problems it is necessary to conduct a study related to predictions. Many

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branches of computer science discuss prediction problems such as Datamining [1]–[5] and Artificial Neural Networks [6]–[9].

Artificial Neural Networks (ANN) is a network consisting of a group of small processing units that are inspired by the human biological nerve cell system modeled based on human neural networks [10], [11]. ANN has the advantage to solve a problem that has the same pattern as the example given so ANN can be used to solve problems that are discrete, real or vector [10]. One algorithm used to make predictions with Artificial Neural Networks is Backpropogation. Backpropogation has the advantage that one of them is to use 2 grooves in weight calculation, namely forward propagation and back propagation [12]. In addition Backpropagation also trains the network to get a balance between the ability of the network to recognize patterns used during training and the ability of networks to provide correct responses to patterns of input that are similar (but not the same) to the patterns used during training [10]. Many studies related to backpropogation conducted by researchers about prediction. One of them is research [13] on State Retail Sukuk. In that study, it was explained that the Backpropogation Algorithm was able to predict the most investors in the purchase of the State Retail Sukuk. Input variables used are Civil Servants (X1), Private Employees (X2), IRT (X3), Entrepreneurs (X4), TNI / Police (X5) and Others (X6) with 4 architectural training and testing models namely 6-2-1, 6-5-1,6-2-5-1 and 6-5-2-1. The best architectural models in the study are 6-5-2-1 with epoch 37535, MSE 0,0009997295 and 100% accuracy. The sensitivity analysis will be done from this model to see which variable has the best performance and obtained the Private Employee (X2) variable with a score of 0.3268. In order to get the most investor prediction results on the purchase of sukuk for the next 008 series based on the profession category are Private Employees. From the description above, it is hoped that this research can predict the Retail Price of Rice in traditional markets by improvising the Adaptive Learning Rate to increase the prediction accuracy value. We know that the prediction accuracy done by previous researchers is purely using the Backpropogation method. The result of the prediction accuracy is the percent level (%). The higher the level of percent (100%) obtained, the better the architecture model is made and vice versa the lower the level of percent (50%) obtained, the worse the architectural model is made. In this case the researchers used improvised Adaptive Learning Rate to predict the retail price of rice in traditional markets using backpropogation. so the results obtained are more leverage to increase the predictive value of previous researchers who did not use Adaptive Learning Rate improvisation. For the government, it is hoped that this research can be useful in providing input on retail rice price predictions that have an impact on rice price stability in Indonesia.

2. Research Methodology

2.1. Artificial intelligence

Artificial Intelligence is the largest contribution in the field of AI, which was preceded by an article from Alan Turing in 1950 entitled Computing Machinery and Intelligence discussing the terms of a machine is considered intelligent [14].

2.2. Artificial Neural Networks

Artificial neural network (ANN) is a network consisting of a group of small processing units that are modeled based on human neural networks that are created as a generalization of mathematical models of human understanding [15].

2.3. Backpropagation Method

Backpropagation model is a supervised leaning technique that is most widely used in dealing with the problem of recognizing complex patterns. Improvised Adaptive Learning Rate is a spontaneous action with a method that aims to increase the effectiveness of learning level parameters that serve to increase the speed of learning from backpropagation [6], [7].

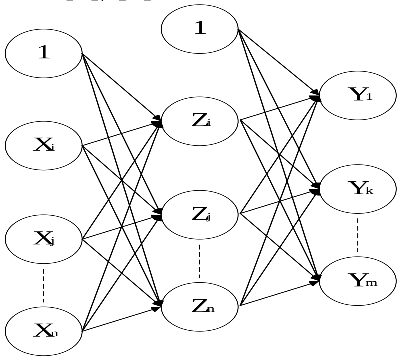

Figure 1. Backpropagation Network Architecture

Research methodology is the stage of conducting research in collecting data or information used in finding solutions to problems as shown in the following flowchat.

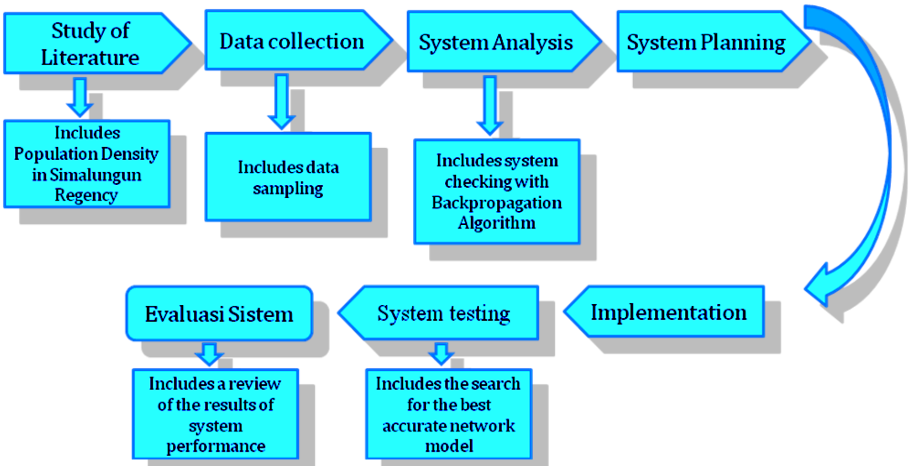

Figure 2. Research Framework

2.4. Data source

The process of using the backpropogation method has two stages where the first stage is pattern recognition by finding the best architecture of the artificial neural network model that is made. The process of training and testing data to get the best model obtained from the Badan Pusat Statistic (BPS) in 33 provinces in Indonesia for the retail price of rice in traditional markets (Rupiah/Kg) for the last 6 years (2011-2016). The second stage is to make predictions with the best architectural patterns obtained in the first stage. The testing process is carried out by entering research data by comparing the minimum error values obtained from the best architectural patterns performed in the first stage.

Table 1. Data on average retail prices of rice in traditional markets

City Retail Price	Average Retail Price of Rice in Traditional Markets in 33 Cities (Rupiah/Kg)					
	2011	2012	2013	2014	2015	2016
Banda Aceh	8247.31	8606.16	9075.62	9330.47	9735.41	10244.09
Medan	7725.61	8601.97	9171.82	9574.73	10146.74	10547.87
Padang	9878.17	9620.26	9558.50	11712.50	12258.02	12789.53
Pekanbaru	9600.82	9601.14	9886.08	11171.72	11711.67	12270.42
Tanjung Pinang	8031.48	9786.41	10321.85	11365.26	12424.87	10573.25
Jambi	7631.13	8710	9159.88	9683.54	10335.91	9644.11
Palembang	7643.67	8407.40	8676.74	8876.55	9644.30	10370.57

Pangkal Pinang	7667.32	8898.21	9291.09	9528.82	10751.58	9966.58
Bengkulu	7556.16	8116.50	8401.98	9696.08	10419.91	11416.46
Bandar Lampung	10574.74	8754.79	8974.06	9817.36	10200.47	13767.38
Jakarta	9929.83	9037.23	9447.22	10027.05	11732.98	12413.75
Bandung	7639.10	8405.67	8571.61	9018.31	10695.56	11231.04
Serang	7761.37	7708.31	7931.05	8151.26	9151.21	10379.40
Semarang	7183.22	8398.18	8791.97	9187.41	9902.22	9872.40
Yogyakarta	7798.90	7902.48	8383.10	9062.10	9771.84	10249.07
Surabaya	6493.79	8335.03	8794.77	9209.61	10132.20	9553.36
Denpasar	8332.57	8647.23	9044.05	9315.86	10378.28	10580.99
Mataram	6609.87	7704.52	7776.14	8576.47	9608	9720.53
Kupang	8058.16	8435.67	8921.70	9127.71	9999.64	11084.87
Pontianak	9116.78	9828.72	10326.79	10814.36	12012.61	12477.20
Palangkaraya	10882.96	11006.28	10742.08	12421.42	14727.73	13813.61
Banjarmasin	9343.89	10127.24	9960.22	11272.31	12533.07	12910.90
Samarinda	8056.50	9053.94	9563.21	11088.35	11429.31	11248.34
Manado	7677.71	8706.13	8901.29	9223.42	10470.17	11665.84
Gorontalo	7014.97	8237.56	8398	8620.03	9362.14	10358.26
Palu	6503.52	7958.49	7949.16	8266.71	9446.11	9924.58
Makassar	6706.13	7501.46	7565.25	7690.31	9040.99	10666.58
Mamuju	7613.73	7489.85	7876.03	8107.55	8826.79	10773.81
Kendari	6889.85	8186.44	8283.12	8446.03	9937.78	9551.98
Ambon	8394.32	8981.29	9381.29	10292.05	11440.15	11818.78
Ternate	8785.25	9462.62	9757	10447.98	11727.36	12030.75
Jayapura	7551.39	10205.05	10325.14	11295.57	12393.81	12376.07
Manokwari	9284.97	9137.30	10013.37	10686.52	11188.78	12965.26

3. Results and Discussion

3.1. Input and Target

Rice retail price data in traditional markets is then processed using the backpropogation method. So that the data can be recognized by artificial neural networks, then the data must be represented in numerical form between 0-1, this is because the network uses the activation function of binary sigmoid (logsig) which has a range of values 0-1.

3.2. Input Variable

Variables are needed as input. In this case the data was obtained from the Badan Pusat Statistic with the subject of retail prices of rice in traditional markets (2011-2016). The data is divided into 2 parts, namely: Training data (2011-2013) and testing data (2014-2016).

3.3. Target Variable

The target variable used in the prediction of the retail price of rice on the traditional market includes: the retail price of rice.

3.4. Output Variable

The expected outcome at this stage is to form the best architectural model for predicting retail prices of rice in traditional markets. The test results are as follows:

a) The output of this prediction is the best architectural pattern in predicting the retail price of rice in traditional markets by looking at minimum errors.
b) Training and testing output categorization is the minimum error level of the target as shown in the following table:

Table 2. Category Data

No	Information	*Error* Minimum
1	True	0.09 between 0.001and -(0.05 between 0.001)
2	False	> 0.09 and > (-0.09)

3.5. Data processing

Data processing is done with the help of the Matlab 6.1 application. The data used is the retail price of rice in the traditional market in 2011-2016. The data is divided into 2 parts, including: Training data (2011-2013) and testing data (2014-2016) as follows:

a) Training Data
   Input (X): Retail price of rice (2011-2012) - 33 provinces
   Output (Y): Rice retail prices for 2013 - 33 provinces
b) Testing Data
   Input (X): Retail price of rice (2011-2012) - 33 provinces
   Output (Y): Rice retail prices for 2013 - 33 provinces

The data is converted to 0-1 because the activation function used is sigmoid biner (logsig). The following is the result of data conversion:

Table 3. Training data (Conversion)

No	City	X1	X2	Y
		2011	2012	2013
1	Banda Aceh	0,2704	0,3052	0,3508
2	Medan	0,2197	0,3048	0,3602
3	Padang	0,4288	0,4038	0,3978
4	Pekanbaru	0,4019	0,4019	0,4296
5	Tanjung Pinang	0,2494	0,4199	0,4719
6	Jambi	0,2105	0,3153	0,3590
7	Palembang	0,2117	0,2859	0,3121
8	Pangkal Pinang	0,2140	0,3336	0,3718
9	Bengkulu	0,2032	0,2577	0,2854
10	Bandar Lampung	0,4965	0,3197	0,3410
11	Jakarta	0,4338	0,3471	0,3870
12	Bandung	0,2113	0,2858	0,3019
13	Serang	0,2232	0,2180	0,2396
14	Semarang	0,1670	0,2850	0,3233
15	Yogyakarta	0,2268	0,2369	0,2836
16	Surabaya	0,1000	0,2789	0,3236
17	Denpasar	0,2787	0,3092	0,3478
18	Mataram	0,1113	0,2176	0,2246
19	Kupang	0,2520	0,2887	0,3359
20	Pontianak	0,3548	0,4240	0,4724
21	Palangkaraya	0,5264	0,5384	0,5128
22	Banjarmasin	0,3769	0,4530	0,4368
23	Samarinda	0,2518	0,3487	0,3982
24	Manado	0,2150	0,3149	0,3339
25	Gorontalo	0,1506	0,2694	0,2850
26	Palu	0,1009	0,2423	0,2414
27	Makassar	0,1206	0,1979	0,2041
28	Mamuju	0,2088	0,1968	0,2343
29	Kendari	0,1385	0,2645	0,2738
30	Ambon	0,2847	0,3417	0,3805
31	Ternate	0,3226	0,3884	0,4170
32	Jayapura	0,2028	0,4606	0,4722
33	Manokwari	0,3712	0,3568	0,4420

Table 4. Testing data (Conversion)

No	City	X1	X2	Y
		2014	2015	2016
1	Banda Aceh	0,3756	0,4150	0,4644
2	Medan	0,3993	0,4549	0,4939
3	Padang	0,6070	0,6600	0,7117
4	Pekanbaru	0,5545	0,6070	0,6613
5	Tanjung Pinang	0,5733	0,6763	0,4964
6	Jambi	0,4099	0,4733	0,4061
7	Palembang	0,3315	0,4061	0,4767
8	Pangkal Pinang	0,3949	0,5137	0,4374
9	Bengkulu	0,4111	0,4815	0,5783
10	Bandar Lampung	0,4229	0,4601	0,8067
11	Jakarta	0,4433	0,6090	0,6752
12	Bandung	0,3453	0,5082	0,5603
13	Serang	0,2610	0,3582	0,4775
14	Semarang	0,3617	0,4312	0,4283
15	Yogyakarta	0,3495	0,4185	0,4649
16	Surabaya	0,3639	0,4535	0,3973
17	Denpasar	0,3742	0,4774	0,4971
18	Mataram	0,3024	0,4026	0,4135
19	Kupang	0,3559	0,4406	0,5461
20	Pontianak	0,5198	0,6362	0,6813
21	Palangkaraya	0,6759	0,9000	0,8112
22	Banjarmasin	0,5643	0,6868	0,7235
23	Samarinda	0,5464	0,5795	0,5619
24	Manado	0,3652	0,4863	0,6025
25	Gorontalo	0,3066	0,3787	0,4755
26	Palu	0,2723	0,3868	0,4333
27	Makassar	0,2163	0,3475	0,5054
28	Mamuju	0,2568	0,3267	0,5158
29	Kendari	0,2897	0,4346	0,3971
30	Ambon	0,4690	0,5806	0,6174
31	Ternate	0,4842	0,6085	0,6380
32	Jayapura	0,5665	0,6732	0,6715
33	Manokwari	0,5074	0,5562	0,7288

Based on the discussion of the introduction to using code in Matlab 6.1 software, the following optimization parameters are used to predict the retail price of rice in traditional markets by improvising the learning rate:

Table 5. Optimization of Backpropagation Parameters

Optimization	
Dataset	Rice retail prices (33 data
Distribution of Dataset	Training (2011-2013) Testing (2014-2016)
Number of layers	*1 input layer* *1 hidden layer* *1 output layer*
Neuron	The number of neurons in the input and hidden layer according to number of dataset inputs with one neuron in the output layer Neurons: 10, 15
Learning rate	0,1; 0,5; 0,9
Target error	0,09 between 0,001

3.6. Architectural Model Training and Testing Results 2-10-1 (Lr=0,1; 0,5; 0,9)

The following are the complete results of training and testing of architectural models 2-10-1 (LR: 0.1; 0.5; 0.9) in graphical form (epoch, MSE Training, MSE Training, Accuracy).

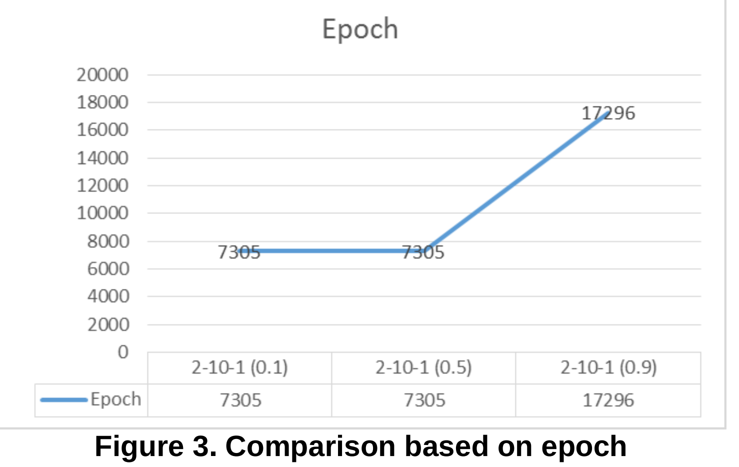

Figure 3. Comparison based on epoch

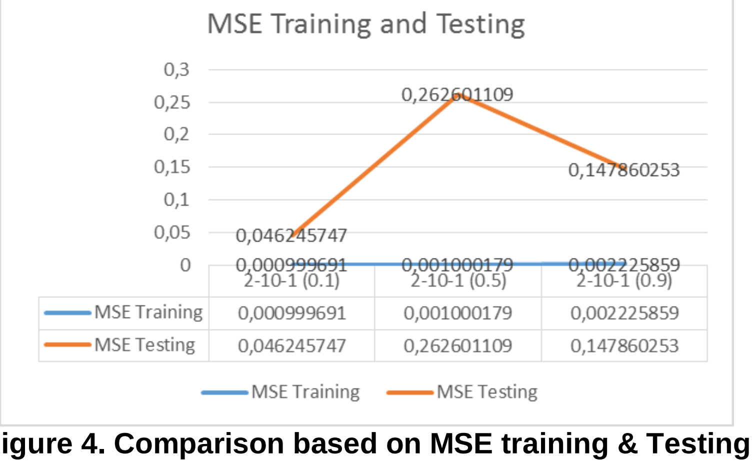

Figure 4. Comparison based on MSE training & Testing

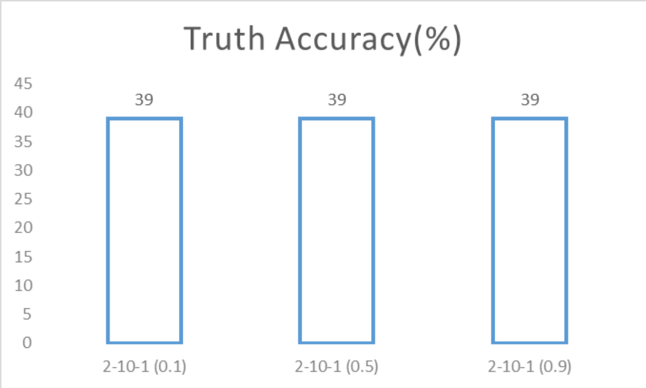

Figure 5. Comparison based on Accuracy

3.7. Architectural Model Training and Testing Results 2-15-1 (Lr=0,1; 0,5; 0,9)

The following are the complete results of training and testing of architectural models 2-15-1 (LR: 0.1; 0.5; 0.9) in graphical form (epoch, MSE Training, MSE Training, Accuracy)

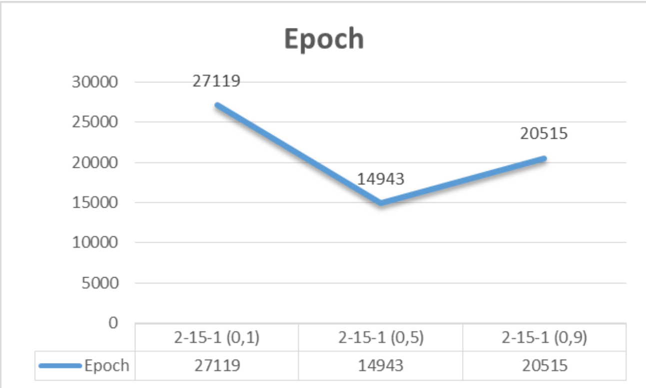

Figure 6. Comparison based on epoch

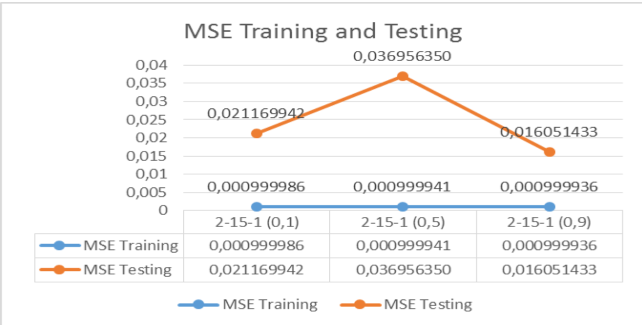

Figure 7. Comparison based on MSE training & Testing

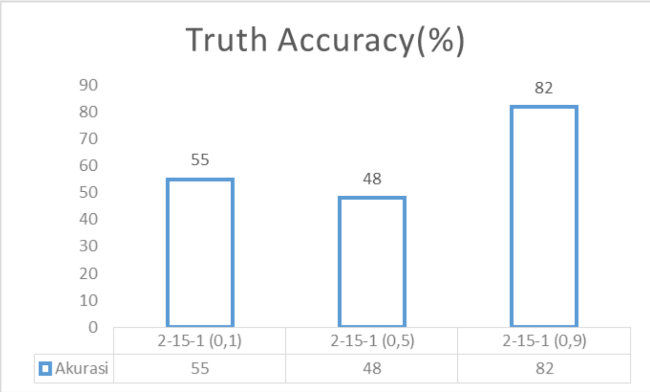

Figure 8. Comparison based on Accuracy

3.8. Selection of the best ANN architectural model

The selection of the best architecture in predicting retail prices of rice in traditional markets by improvising the learning rate using 2 models (2-10-1 and 2-15-1) using the Matlab 6.1 application software has different results both in terms of epoch, accuracy, MSE training and MSE testing. From these 2 models, improvised learning rate was carried out at LR: 0.1; 0.5 and 0.9. The following is a complete recapitulation in the following table:

Table 6. Recapitulation of Architectural Models

Architecture	LR	Epoch	MSE Training	MSE Testing	Accuracy
2-10-1	0.1	7305	0,000999691	0,046245747	39%
2-10-1	0.5	7305	0,001000179	0,262601109	39%
2-10-1	0.9	17296	0,002225859	0,147860253	39%
2-15-1	0.1	27119	0,000999986	0,021169942	55%
2-15-1	0.5	14943	0,000999941	0,036956350	48%
2-15-1	0.9	20515	0,000999936	0,016051433	82%

Based on the table, the selection of the best architectural model is 2-15-1 with an accuracy rate of 82%, MSE Training 0,000999936, MSE Testing 0.016051433 and Epoch 20515. In this case increasing accuracy for testing with improvised learning rate can be done for cases Predicted retail price of rice in traditional markets.

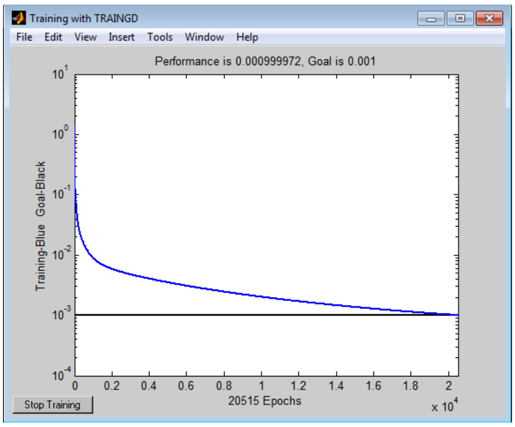

Figure 9. Architecture 2-15-1 achieving Goal (LR: 0.9)

4. Conclusion

The results of these studies can be concluded:

a) Artificial neural networks with backpropogation methods can be applied to predict the retail price of rice in traditional markets by improvising the learning rate. Data was obtained from the Central Statistics Agency (BPS) in 33 provinces in Indonesia for the retail price of rice in traditional markets (Rupiah / Kg) for the past 6 years (2011-2016). By improvising the learning rate using 2 models including: 2-10-1 and 2-15-1 (Lr: 0.1; 0.5; 0.9) the best architectural model is obtained 2-15-1 (Lr: 0.9) with an accuracy rate of 82%, MSE Training 0,000999936, MSE Testing 0.016051433 and Epoch 20515.

b) From a series of model trials, adding learning case predictions of retail prices of rice in traditional markets with backpropogation has increased the value of truth accuracy

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