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
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 Backpropagation. Backpropagation 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 backpropagation conducted by researchers about prediction. One of them is research [13] on State Retail Sukuk. In that study, it was explained that the Backpropagation 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 Backpropagation 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 backpropagation. 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].

![Backpropagation Network Architecture](image)

**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 flowchart.

![Flowchart](image)

**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          | 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|


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 0.001 and (-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     |
|----|---------------|-----|-----|-------|
| 1  | Banda Aceh    | 0.2704 | 0.5052 | 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 Pina  | 0.2494 | 0.4199 | 0.4719 |
| 6  | Jambi         | 0.2105 | 0.3153 | 0.3590 |
| 7  | Palambang     | 0.2117 | 0.2859 | 0.3121 |
| 8  | Pangkal Pinan | 0.2140 | 0.3336 | 0.3718 |
| 9  | Bengkulu      | 0.2032 | 0.2577 | 0.2854 |
| 10 | Bandar Lampun | 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        | 0.3520 | 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       | 0.3185 | 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     |
|----|---------------|-----|-----|-------|
| 1  | Banda Aceh    | 0.3756 | 0.4150 | 0.4644 |
| 2  | Medan         | 0.3993 | 0.4549 | 0.4939 |
| 3  | Padang        | 0.6070 | 0.6060 | 0.7117 |
| 4  | Pekanbaru     | 0.5545 | 0.6070 | 0.6613 |
| 5  | Tanjung Pina  | 0.5733 | 0.6763 | 0.4964 |
| 6  | Jambi         | 0.4099 | 0.4733 | 0.4061 |
| 7  | Palambang     | 0.3315 | 0.4061 | 0.4767 |
| 8  | Pangkal Pinan | 0.3949 | 0.5137 | 0.4374 |
| 9  | Bengkulu      | 0.4111 | 0.4815 | 0.5783 |
| 10 | Bandar Lampun | 0.4229 | 0.4601 | 0.8067 |
| 11 | Jakarta       | 0.4433 | 0.0090 | 0.6752 |
| 12 | Bandung       | 0.3453 | 0.5082 | 0.5603 |
| 13 | Serang        | 0.2610 | 0.3382 | 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** |
| **Distribution of Dataset** | Rice retail prices (33 data) |
| **Number of layers** | Dataset |
| | Training (2011-2013) |
| | Testing (2014-2016) |
| **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 Testing, Accuracy).

![Figure 3. Comparison based on epoch](image_url)

![Figure 4. Comparison based on MSE training & Testing](image_url)
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
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:

| Architecture | LR   | Epoch | MSE Training  | MSE Testing  | Accuracy |
|--------------|------|-------|---------------|--------------|----------|
| 2-10-1       | 0.1  | 7305  | 0.0009999691  | 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.

4. Conclusion

The results of these studies can be concluded:

a) Artificial neural networks with backpropagation 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 0.00099936, 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 backpropagation has increased the value of truth accuracy.

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