Backpropagation Network Optimization Using One Step Secant (OSS) Algorithm

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Abstract. Education is one of the main indicators in national development efforts. The government in its efforts to realize national goals to educate the nation's life has made a policy for compulsory 9-year schools, namely elementary and junior high schools. To find out how many residents use the education facilities provided by the government can be seen through school enrollment rates (SPR). A high School Participation Rate (SPR) means showing greater opportunities to access education in general. This study aims to optimize artificial neural networks with the One Step Secant (OSS) algorithm. Artificial Neural Network (ANN) is part of the artificial intelligence system (Artificial Intelligence, AI) which is one of the artificial representations of the human brain that always tries to simulate the learning process in the human brain. The sample data used for optimization is SPR Indonesia data by province. Using 4 architectural models with 5 input variables, 1 shadow layer and 1 output. The best results obtained between architectures 5-4-1, 5-8-1, 5-16-1 and 5-32-1 are architectures 5-16-1. Obtained prediction accuracy comparisons using the One Step Secant (OSS) algorithm and standard algorithms namely 96.97% and 100%. The standard algorithm is superior in accuracy, the One Step Secant (OSS) algorithm is superior in terms of iterations.

1. Introduction

Education is one of the main indicators in national development efforts. According to Law No. 20 of 2003 concerning the National Education System, education is a conscious and planned effort to create a learning atmosphere and learning process so that students actively develop their potential to have religious spiritual strength, self-control, personality, intelligence, noble character, and skills needed by themselves, society, nation and state.

The government in its efforts to realize national goals to educate the nation's life has made a policy for compulsory 9-year schools, namely elementary and junior high schools. To find out how many residents use the education facilities provided by the government can be seen through School Participation Rate (SPR). A high School Participation Rate (SPR) means showing greater opportunities to access education in general. The importance of education in building human resources must be a mature calculation to manage it. One way to maximize business in the future is to know the picture that happened first. Accurate and accurate predictions can be a benchmark for seeing the future.

In computer science there is a technique that can be used to predict the future, namely Artificial Neural Networks (ANN) using the backpropagation method. This method is a very good method of
dealing with the problem of recognizing complex patterns. But the standard backpropagation algorithm tends to be slow to reach convergence in getting maximum results. Therefore this algorithm can still be optimized to improve the results of accuracy. The One Step Secant (OSS) algorithm is an algorithm that can train any network during weight, the net input and activation functions have derivative functions. This algorithm will maximize time and increase the accuracy produced by standard backpropagation.

The object that will be predicted in this study is the school Participation rate (EPR) in education coverage aged 19 to 24 years, namely in higher education. To calculate school Participation numbers, a formula can be used:

\[
EPR_{19-24} = \frac{\text{Number of residents aged 19-24 years who are still in school}}{\text{Number of residents aged 19-24 years}} \times 100\% \tag{1}
\]

In a previous study, [1] [2] conducted a study to look at the factors that influence SPR, namely the teacher to student ratio, poverty rate and income per capita that have a significant effect on the SPR. This study produced a correlation between SPR and the social conditions of the community. The relationship formed is negative where if the poverty level increases, the SPR will decrease.

2. Method

2.1. Artificial Intelligence

Artificial intelligence is one area that is quite reliable in solving problems such as prediction (forecasting) [1]. AI is a very important discipline and it includes a number of well recognized and mature areas including Neural Network [2]–[4]. Artificial Intelligence (AI) is a general term that implies the use of a computer to model intelligent behavior with minimal human intervention. AI is generally accepted as having started with the invention of robots. The term derives from the Czech word robota, meaning biosynthetic machines used as forced labor [5].

2.2. Artificial Neural Network

Artificial Neural Network (ANN) is one of the studies of Artificial Intelligence and is a new computing technology in the field of computer science study. Neural networks mostly used for problem-solving in pattern recognition, data analysis, control and clustering [6][7]. Initially ANN were developed in the field of artificial intelligence and were first introduced for image recognition. The central concept was inspired by knowledge of the nervous system, especially the human brain with its closely connected neurons [8][9].

2.3. Backpropagation Neural Network

Backpropagation (BP) algorithm was used to develop the ANN model [10][11]. The typical topology of BPANN (Backpropagation Artificial Neural Network) involves three layers: input layer, where the data are introduced to the network; hidden layer, where the data are processed; and output layer, where the results of the given input are produced [12]–[14]. A backpropagation algorithm was used for training. It is a convenient and simple iterative algorithm that usually performs well, even with complex data. Unlike other learning algorithms (like Bayesian learning) it has good computational properties when dealing with largescale data [15][16].

2.4. Backpropagation Architecture

The back-propagation learning algorithm (BPLA) has become famous learning algorithms among ANNs. In the learning process, to reduce the inaccuracy of ANNs, BPLAs use the gradient-decent search method to adjust the connection weights. The structure of a back-propagation ANN is shown in Figure 2. The output of each neuron is the aggregation of the numbers of neurons of the 3 previous level multiplied by its corresponding weights. The input values are converted into output signals with the calculations of activation functions. Backpropagation ANNs have been widely and successfully applied in diverse applications, such as pattern recognition, location selection and performance evaluations [17][18].
2.5. Data Analysis
The data used in this study is the data of SPR ages 19-24 years by province obtained from the National Statistics Agency (bps.go.id). The data used is data from 2011 to 2017. The following is the data used in this study can be seen in table 1.

| The Province       | 2011  | 2012  | 2013  | 2014  | 2015  | 2016  | 2017  |
|--------------------|-------|-------|-------|-------|-------|-------|-------|
| Aceh               | 27.68 | 28.55 | 29.18 | 32.93 | 33.07 | 33.94 | 34.28 |
| Sumatera Utara     | 16.94 | 17.27 | 21.81 | 24.82 | 25.16 | 26.62 | 26.8  |
| Sumatera Barat     | 23.95 | 27.55 | 30.66 | 32.89 | 33.13 | 34.71 | 35.45 |
| Riau               | 15.34 | 15.81 | 22.04 | 24.48 | 24.85 | 26.18 | 27.28 |
| Jambi              | 15.64 | 15.22 | 20.25 | 22.11 | 22.22 | 23.86 | 24.12 |
| Sumatera Selatan   | 12.75 | 13.91 | 14.08 | 16.87 | 17    | 18.07 | 19.17 |
| Bengkulu           | 17.02 | 19.64 | 24.12 | 28.14 | 28.37 | 28.93 | 29.9  |
| Lampung            | 10.39 | 11.9  | 16.19 | 18.67 | 18.81 | 19.72 | 20.96 |
| Bangka             | 8.63  | 9.3   | 9.46  | 12.22 | 12.73 | 13.81 | 14.99 |
| Belitung Kep, Riau | 9.67  | 10.14 | 14.85 | 17.4  | 17.69 | 18.58 | 19.13 |
| DKI Jakarta        | 17.83 | 18.02 | 19.65 | 22.52 | 22.71 | 23.06 | 24.6  |
| Jawa Barat         | 11.15 | 12.25 | 17.34 | 19.27 | 19.4  | 20.37 | 21.5  |
| Jawa Tengah Yogyakarta | 44.17 | 44.69 | 45.86 | 49.08 | 49.17 | 49.95 | 51.33 |
| Jawa Timur Banten  | 13.56 | 15.97 | 18.08 | 19.61 | 19.68 | 20.74 | 21.33 |
| Bali               | 18.93 | 18.99 | 19.84 | 23.59 | 23.75 | 25.36 | 26.56 |
| Nusa Tenggara Barat | 16.99 | 17.82 | 22.64 | 26.73 | 26.84 | 27.79 | 28.52 |
| Nusa Tenggara Timur | 17   | 17.92 | 22.88 | 26.22 | 26.54 | 26.75 | 27.8  |
| Kalimantan Barat   | 11.94 | 14.17 | 19.27 | 23.18 | 23.32 | 24.75 | 25.8  |
| Kalimantan Tengah  | 13.05 | 14.04 | 19.89 | 22.31 | 22.47 | 22.72 | 24.15 |
| Kalimantan Tengah Selatan | 13.62 | 16.48 | 16.95 | 20.36 | 20.53 | 21.89 | 23.53 |
| Kalimantan Tengah Selatan | 16.92 | 20.33 | 25.04 | 27.34 | 27.55 | 28.88 | 30.04 |
| Sulawesi Utara     | 15.16 | 16.12 | 16.36 | 20.91 | 21.31 | 22.82 | 24.22 |
| Sulawesi Tengah    | 16.72 | 16.74 | 21.76 | 25.05 | 25.13 | 25.57 | 26.31 |
| Sulawesi Tengah Selatan | 21.46 | 23.17 | 27.8 | 30.23 | 30.64 | 31.48 | 32.16 |
| Sulawesi Tengah Gorontalo | 21.48 | 23.62 | 24 | 28.78 | 28.89 | 29.31 | 30.03 |
| Sulawesi Barat     | 13.03 | 14.65 | 18.04 | 21.53 | 21.97 | 22.36 | 23.49 |
| Maluku             | 26.71 | 28.98 | 33.8  | 36.44 | 36.6  | 37.51 | 38.2  |
3. Results and discussion

3.1. Input and Target Data Transformation

The original data is pre-processed by artificial neural networks with the backpropagation method, in order to be understood, the data must be converted into numbers between 0 and 1 using the formula:

\[ x' = \left( \frac{0.05 \times (x - x_{\text{min}})}{x_{\text{max}} - x_{\text{min}}} \right) + 0.1 \]  

(2)

where:
- \( x' \) = Transformation Results
- \( x \) = Original Data
- \( x_{\text{min}} \) = Minimum Data
- \( x_{\text{max}} \) = Maximum Data

For training data used SPR data based on provinces with 5 input data, namely data from 2011 to 2015 with a target for 2016 while for testing data using 5 input data, namely data from 2012 to 2016 with a target for 2017, transformation of training and testing data is shown in Tables 2 and 3.

| Table 2. Training Data |
|------------------------|
| Data | X1 | X2 | X3 | X4 | X5 | Target |
|------|----|----|----|----|----|--------|
| Data 1 | 0.45691 | 0.47321 | 0.48501 | 0.55527 | 0.55789 | 0.57419 |
| Data 2 | 0.25569 | 0.26187 | 0.34693 | 0.40333 | 0.40970 | 0.43705 |
| Data 3 | 0.38703 | 0.45447 | 0.51274 | 0.55452 | 0.55902 | 0.58862 |
| Data 4 | 0.22571 | 0.23452 | 0.35124 | 0.39696 | 0.40389 | 0.42881 |
| Data 5 | 0.23133 | 0.22347 | 0.31770 | 0.35255 | 0.35461 | 0.38534 |
| Data 6 | 0.17719 | 0.19892 | 0.20211 | 0.25438 | 0.25681 | 0.27668 |
| Data 7 | 0.25719 | 0.30628 | 0.39021 | 0.46553 | 0.46984 | 0.48033 |
| Data 8 | 0.13297 | 0.16126 | 0.24164 | 0.28810 | 0.29073 | 0.30778 |
| Data 9 | 0.10000 | 0.11255 | 0.11555 | 0.16726 | 0.17681 | 0.19705 |
| Data 10 | 0.11948 | 0.12829 | 0.21653 | 0.26431 | 0.26974 | 0.28642 |
| Data 11 | 0.27237 | 0.27593 | 0.30646 | 0.36023 | 0.36379 | 0.37035 |
| Data 12 | 0.14721 | 0.16782 | 0.26319 | 0.29934 | 0.30178 | 0.31995 |
| Data 13 | 0.15396 | 0.15995 | 0.26468 | 0.32201 | 0.32370 | 0.34281 |
| Data 14 | 0.76585 | 0.77560 | 0.79752 | 0.85785 | 0.85953 | 0.87415 |
| Data 15 | 0.17607 | 0.21166 | 0.30347 | 0.34749 | 0.34956 | 0.36304 |
| Data 16 | 0.19237 | 0.23752 | 0.27705 | 0.30571 | 0.30703 | 0.32689 |
| Data 17 | 0.29297 | 0.29410 | 0.31002 | 0.38028 | 0.38328 | 0.41344 |
| Data 18 | 0.25663 | 0.27218 | 0.36248 | 0.43911 | 0.44117 | 0.45897 |
### Table 3. Testing Data

| Data | X1   | X2   | X3   | X4   | X5   | Target |
|------|------|------|------|------|------|--------|
| Data 1 | 0.47321 | 0.48503 | 0.55527 | 0.55789 | 0.57419 | 0.58056 |
| Data 2 | 0.26187 | 0.34693 | 0.40333 | 0.40970 | 0.43705 | 0.44042 |
| Data 3 | 0.45447 | 0.51274 | 0.55452 | 0.55902 | 0.58862 | 0.60248 |
| Data 4 | 0.23452 | 0.35124 | 0.39696 | 0.40389 | 0.42881 | 0.44941 |
| Data 5 | 0.22347 | 0.31770 | 0.35255 | 0.35461 | 0.38534 | 0.39021 |
| Data 6 | 0.19892 | 0.20211 | 0.25438 | 0.25681 | 0.27686 | 0.29747 |
| Data 7 | 0.30628 | 0.39021 | 0.46553 | 0.46984 | 0.48033 | 0.49850 |
| Data 8 | 0.16126 | 0.24164 | 0.28810 | 0.29073 | 0.30778 | 0.33101 |
| Data 9 | 0.11255 | 0.11555 | 0.16726 | 0.17681 | 0.19705 | 0.21916 |
| Data 10 | 0.12829 | 0.21653 | 0.26431 | 0.26974 | 0.28642 | 0.29672 |
| Data 11 | 0.27593 | 0.30646 | 0.36023 | 0.36379 | 0.37035 | 0.39920 |
| Data 12 | 0.16782 | 0.26319 | 0.29934 | 0.30178 | 0.31995 | 0.34112 |
| Data 13 | 0.15995 | 0.26468 | 0.32201 | 0.32370 | 0.34281 | 0.35293 |
| Data 14 | 0.77560 | 0.79752 | 0.85785 | 0.85953 | 0.87415 | 0.90000 |
| Data 15 | 0.21166 | 0.30347 | 0.34749 | 0.34956 | 0.36304 | 0.37560 |
| Data 16 | 0.23752 | 0.27705 | 0.30571 | 0.30703 | 0.32689 | 0.33794 |
| Data 17 | 0.29410 | 0.31002 | 0.38028 | 0.38328 | 0.41344 | 0.43593 |
| Data 18 | 0.27218 | 0.36248 | 0.43911 | 0.44117 | 0.45897 | 0.47265 |
| Data 19 | 0.27405 | 0.36698 | 0.42956 | 0.43555 | 0.43948 | 0.45916 |
3.2. **Defining Output**

The expected results at this defining stage are to look for patterns to determine the best value to predict. The test results are as follows:

a. The output of this prediction is the best architectural pattern to predict the amount of rice production by province by looking at the minimum error.

b. Categorization of training output (train) and testing (test)

The category for output is determined by the minimum error rate of the target, the categories are listed in Table 4.

| No | Explanation | Minimum Error |
|----|-------------|---------------|
| 1  | True        | ≤ 0.05        |
| 2  | False       | > 0.05        |

3.3. **Result**

This study implements several architectures to obtain optimal results, the architecture (model) used can is summarized in Table 5:

| Table 5. Architectural design |
|-------------------------------|
| Characteristics | Specification |
| Architectural     | 1 *hidden layer* |
| Input Data        | 5               |
| Hidden Layer      | 4, 8, 16, 32    |
| Goal              | 0.01            |
| Maximum Epochs    | 100000          |
| Learning rate     | 0.01            |
Each of the architecture is processed using the standard backpropagation algorithm and the One Step Secant (OSS) algorithm. The best architecture can be seen from the accuracy of the truth, a little more epochs and the size of the MSE. The following is the accuracy data, the number of epochs and MSE from the tested model.

**Table 6. Comparison of Standard Backpropagation with Backpropagation with One Step Secant (OSS)**

| Model  | Criteria | Standard | OSS  |
|--------|----------|----------|------|
| 5-4-1  | Accuracy | 93,94%   | 96,97% |
|        | MSE      | 0,012766 | 0,004864 |
|        | Epochs   | 68       | 4    |
| 5-8-1  | Accuracy | 96,97%   | 96,97% |
|        | MSE      | 0,009094 | 0,01385 |
|        | Epochs   | 69       | 9    |
| 5-16-1 | Accuracy | 100%     | 100%  |
|        | MSE      | 0,010414 | 0,008030 |
|        | Epochs   | 27       | 2    |
| 5-32-1 | Accuracy | 100%     | 96,97% |
|        | MSE      | 0,008179 | 0,009440 |
|        | Epochs   | 39       | 5    |

From the results above it can be seen that the best model that can be used to predict is the 5-16-1 architectural model with 100% accuracy.

*Figure 1. Model 5-16-1 Training Results with Matlab R2011A*
3.4. **Prediction of School Participation Rates**

By using the best architecture that has been obtained, the prediction of SPR is based on the province with the following results:

![Performance Model 5-16-1 with Matlab R2011A](Image)

**Figure 2.** Performance Model 5-16-1 with Matlab R2011A

| Province            | Prediction | Target | Output | Error  | SSE   |
|---------------------|------------|--------|--------|--------|-------|
| Aceh                | 42.0635    | 0.72639| 0.81571| -0.08932| 0.00798|
| Sumatera Utara      | 33.3170    | 0.56252| 0.67602| -0.1150 | 0.01288|
| Sumatera Barat      | 42.0184    | 0.72554| 0.81987| -0.09433| 0.00890|
| Riau                | 33.0966    | 0.55839| 0.66876| -0.11037| 0.01218|
| Jambi               | 31.3296    | 0.52529| 0.63753| -0.11224| 0.01260|
| Sumatera Selatan    | 18.1990    | 0.27928| 0.41214| -0.13286| 0.01765|
| Bangkulu            | 34.9601    | 0.59330| 0.71355| -0.12025| 0.01446|
| Lampung             | 20.9946    | 0.33166| 0.51812| -0.18646| 0.03477|
| Kep, Bangka Belitung| 11.6416    | 0.15642| 0.23226| -0.07584| 0.00575|
| Kep, Riau           | 18.2126    | 0.27953| 0.43566| -0.15613| 0.02438|
| Dki Jakarta         | 31.6809    | 0.53187| 0.65068| -0.11881| 0.01412|
| Jawa Barat          | 23.6838    | 0.38204| 0.55616| -0.17412| 0.03032|
| Jawa Tengah         | 22.7233    | 0.36404| 0.58578| -0.22174| 0.04917|
| Di Yogyakarta       | 50.9297    | 0.89250| 0.90668| -0.01418| 0.00020|
| Jawa Timur          | 28.7599    | 0.47714| 0.63751| -0.16037| 0.02572|
| Banten              | 28.5603    | 0.47340| 0.57365| -0.10025| 0.01005|
| Bali                | 32.0137    | 0.53810| 0.65621| -0.11811| 0.01395|
| Nusa Tenggara Barat| 33.0721    | 0.55793| 0.69982| -0.14189| 0.02013|
| Nusa Tenggara Timur| 34.2631    | 0.58024| 0.69833| -0.11809| 0.01394|
| Kalimantan Barat    | 26.6172    | 0.43700| 0.65034| -0.21334| 0.04551|
| Kalimantan Tengah   | 28.5604    | 0.47340| 0.65104| -0.17764| 0.03155|
| Kalimantan Selatan  | 25.8532    | 0.42268| 0.58185| -0.15917| 0.02534|
| Kalimantan Timur    | 37.3613    | 0.63829| 0.70193| -0.06364| 0.00405|
| Sulawesi Utara      | 23.5823    | 0.38014| 0.58174| -0.20160| 0.04064|

Table 7. Prediction with OSS algorithm
### Table 8. Prediction with standard algorithm

| No. | The Province                        | Prediction | Target | Output | Error | See  |
|-----|-------------------------------------|------------|--------|--------|-------|------|
| 1   | Aceh                                | 30.8526    | 0.51635| 0.61903| -0.10265| 0.01054|
| 2   | Sumatera Utara                      | 31.4041    | 0.52668| 0.61474| -0.08806| 0.00775|
| 3   | Sumatera Barat                      | 30.1669    | 0.50350| 0.61973| -0.11623| 0.01351|
| 4   | Riau                                | 31.5960    | 0.53428| 0.60797| -0.07769| 0.00604|
| 5   | Jambi                               | 32.7102    | 0.55115| 0.63314| -0.08199| 0.00672|
| 6   | Sumatera Selatan                    | 23.7577    | 0.38342| 0.51954| -0.13612| 0.01853|
| 7   | Bengkulu                            | 29.5445    | 0.49184| 0.58951| -0.09767| 0.00954|
| 8   | Lampung                             | 25.9695    | 0.42486| 0.59445| -0.16959| 0.02876|
| 9   | Kep. Bangka Belitung                | 16.6250    | 0.24979| 0.34991| -0.10012| 0.01002|
| 10  | Kep. Riau                           | 23.5082    | 0.37875| 0.53794| -0.15919| 0.02534|
| 11  | Dki Jakarta                         | 33.1127    | 0.55889| 0.64062| -0.08193| 0.00671|
| 12  | Jawa Barat                          | 28.3444    | 0.46936| 0.61792| -0.14856| 0.02207|
| 13  | Jawa Tengah                         | 26.5437    | 0.43562| 0.62673| -0.19111| 0.03652|
| 14  | Di Yogyakarta                       | 42.5008    | 0.73458| 0.76966| -0.03508| 0.00123|
| 15  | Jawa Timur                          | 31.1146    | 0.52126| 0.64590| -0.12464| 0.01554|
| 16  | Banten                              | 32.7348    | 0.55161| 0.63027| -0.07866| 0.00619|
| 17  | Bali                                | 31.7920    | 0.53395| 0.61437| -0.08042| 0.00647|
| 18  | Nusa Tenggara Barat                | 29.4290    | 0.48968| 0.60594| -0.11626| 0.01352|
| 19  | Nusa Tenggara Timur                 | 31.2334    | 0.52348| 0.61693| -0.09345| 0.00873|
| 20  | Kalimantan Barat                    | 27.6106    | 0.45561| 0.62074| -0.16513| 0.02727|
| 21  | Kalimantan Tengah                   | 30.6152    | 0.51190| 0.64717| -0.13527| 0.01830|
| 22  | Kalimantan Selatan                  | 29.5870    | 0.49264| 0.61355| -0.12091| 0.01462|

**MSE**

96.97%

9.21878
4. Conclusion

The conclusion obtained from the research:
1. The iterations needed by the One Step Secant algorithm are fewer than the standard algorithms,
2. The more hidden layers not necessarily the results will be better.
3. The accuracy of the OSS algorithm and standards is not much different and even most standard algorithms have higher accuracy.

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