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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 (EPR). 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:

$$EPR\ 19-24\ = \frac{Number\ of\ residents\ aged\ 19{-}24\ years\ who\ are\ still\ in\ school}{Number\ of\ residents\ aged\ 19{-}24\ years}\ x\ 100\%\ (1)$$

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. Backpropogation 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.

Table 1. Data on School Participation Rates Ages 19 – 24 years

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 Belitung	8,63	9,3	9,46	12,22	12,73	13,81	14,99
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	11,51	11,83	17,42	20,48	20,57	21,59	22,13
Yogyakarta	44,17	44,69	45,86	49,08	49,17	49,95	51,33
Jawa Timur	12,69	14,59	19,49	21,84	21,95	22,67	23,34
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	17,4	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 Selatan	13,62	16,48	16,95	20,36	20,53	21,89	23,53
Kalimantan Timur	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 Selatan	21,46	23,17	27,8	30,23	30,64	31,48	32,16
Sulawesi Tenggara	21,48	23,62	24	28,78	28,89	29,31	30,03
Gorontalo	19,85	20,46	23,27	27,94	28,38	28,98	29,21
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

Maluku Utara	19,33	21,79	26,42	30,85	31,25	31,75	32,1
Papua Barat	16,46	20,03	24,1	29,66	29,96	31,45	31,92
Papua	12,81	13,86	17,5	22,48	22,55	23,75	24,57

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:

$$x' = \left(\frac{0{,}8*(x - x_{min})}{(x_{max} - x_{min})}\right) + 0{,}1 \qquad (2)$$

where :

x' = Transformation Results
x = Original Data
x_{min} = Minimum Data
x_{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	0,27686
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

Data 19	0,26431	0,27405	0,36698	0,42956	0,43555	0,43948
Data 20	0,16201	0,20379	0,29934	0,37260	0,37522	0,40201
Data 21	0,18281	0,20136	0,31096	0,35630	0,35930	0,36398
Data 22	0,19349	0,24707	0,25588	0,31977	0,32295	0,34843
Data 23	0,25532	0,31920	0,40745	0,45054	0,45447	0,47939
Data 24	0,22234	0,24033	0,24482	0,33007	0,33756	0,36585
Data 25	0,25157	0,25194	0,34600	0,40763	0,40913	0,41738
Data 26	0,34037	0,37241	0,45916	0,50468	0,51237	0,52810
Data 27	0,34075	0,38084	0,38796	0,47752	0,47958	0,48745
Data 28	0,31021	0,32164	0,37429	0,46178	0,47002	0,48126
Data 29	0,18244	0,21279	0,27630	0,34169	0,34993	0,35724
Data 30	0,43874	0,48126	0,57157	0,62103	0,62403	0,64108
Data 31	0,30047	0,34656	0,43330	0,51630	0,52379	0,53316
Data 32	0,24670	0,31358	0,38984	0,49400	0,49963	0,52754
Data 33	0,17831	0,19799	0,26618	0,35948	0,36080	0,38328

Table 3. Testing Data

Data	X1	X2	X3	X4	X5	Target
Data 1	0,47321	0,48501	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

Data 20	0,20379	0,29934	0,37260	0,37522	0,40201	0,42169
Data 21	0,20136	0,31096	0,35630	0,35930	0,36398	0,39077
Data 22	0,24707	0,25588	0,31977	0,32295	0,34843	0,37916
Data 23	0,31920	0,40745	0,45054	0,45447	0,47939	0,50112
Data 24	0,24033	0,24482	0,33007	0,33756	0,36585	0,39208
Data 25	0,25194	0,34600	0,40763	0,40913	0,41738	0,43124
Data 26	0,37241	0,45916	0,50468	0,51237	0,52810	0,54084
Data 27	0,38084	0,38796	0,47752	0,47958	0,48745	0,50094
Data 28	0,32164	0,37429	0,46178	0,47002	0,48126	0,48557
Data 29	0,21279	0,27630	0,34169	0,34993	0,35724	0,37841
Data 30	0,48126	0,57157	0,62103	0,62403	0,64108	0,65400
Data 31	0,34656	0,43330	0,51630	0,52379	0,53316	0,53972
Data 32	0,31358	0,38984	0,49400	0,49963	0,52754	0,53635
Data 33	0,19799	0,26618	0,35948	0,36080	0,38328	0,39864

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.

Table 4. Categorization data

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

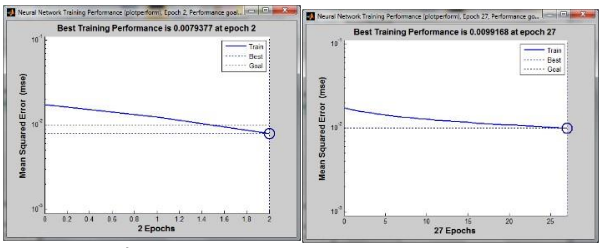

Figure 2. Performance Model 5-16-1 with Matlab R2011A

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:

Table 7. Prediction with OSS algorithm

Backpropagation Algorithm One Step Secant						
No	**The Province**	**Prediction**	**Target**	**Output**	**Error**	**Sse**
1	Aceh	42,0635	0,72639	0,81571	-0,08932	0,00798
2	Sumatera Utara	33,3170	0,56252	0,67602	-0,11350	0,01288
3	Sumatera Barat	42,0184	0,72554	0,81987	-0,09433	0,00890
4	Riau	33,0966	0,55839	0,66876	-0,11037	0,01218
5	Jambi	31,3296	0,52529	0,63753	-0,11224	0,01260
6	Sumatera Selatan	18,1990	0,27928	0,41214	-0,13286	0,01765
7	Bengkulu	34,9601	0,59330	0,71355	-0,12025	0,01446
8	Lampung	20,9946	0,33166	0,51812	-0,18646	0,03477
9	Kep, Bangka Belitung	11,6416	0,15642	0,23226	-0,07584	0,00575
10	Kep, Riau	18,2126	0,27953	0,43566	-0,15613	0,02438
11	Dki Jakarta	31,6809	0,53187	0,65068	-0,11881	0,01412
12	Jawa Barat	23,6838	0,38204	0,55616	-0,17412	0,03032
13	Jawa Tengah	22,7233	0,36404	0,58578	-0,22174	0,04917
14	Di Yogyakarta	50,9297	0,89250	0,90668	-0,01418	0,00020
15	Jawa Timur	28,7599	0,47714	0,63751	-0,16037	0,02572
16	Banten	28,5603	0,47340	0,57365	-0,10025	0,01005
17	Bali	32,0137	0,53810	0,65621	-0,11811	0,01395
18	Nusa Tenggara Barat	33,0721	0,55793	0,69982	-0,14189	0,02013
19	Nusa Tenggara Timur	34,2631	0,58024	0,69833	-0,11809	0,01394
20	Kalimantan Barat	26,6172	0,43700	0,65034	-0,21334	0,04551
21	Kalimantan Tengah	28,5604	0,47340	0,65104	-0,17764	0,03155
22	Kalimantan Selatan	25,8532	0,42268	0,58185	-0,15917	0,02534
23	Kalimantan Timur	37,3613	0,63829	0,70193	-0,06364	0,00405
24	Sulawesi Utara	23,5823	0,38014	0,58174	-0,20160	0,04064

25	Sulawesi Tengah	32,5041	0,54729	0,68947	-0,14218	0,02022
26	Sulawesi Selatan	38,5247	0,66009	0,76787	-0,10778	0,01162
27	Sulawesi Tenggara	35,8477	0,60993	0,72314	-0,11321	0,01282
28	Gorontalo	34,1229	0,57762	0,71308	-0,13546	0,01835
29	Sulawesi Barat	25,2334	0,41107	0,61657	-0,20550	0,04223
30	Maluku	42,8217	0,74059	0,85322	-0,11263	0,01269
31	Maluku Utara	35,2826	0,59935	0,76311	-0,16376	0,02682
32	Papua Barat	32,3408	0,54423	0,71475	-0,17052	0,02908
33	Papua	22,6007	0,36175	0,62994	-0,26819	0,07193
Accuracy						96,97%
MSE						0,021878

Table 8. Prediction with standard algorithm

Algorithm Backpropagation Standar						
No	**The Province**	**Prediction**	**Target**	**Output**	**Error**	**Sse**
1	Aceh	30,8526	0,51635	0,61903	-0,10268	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	0,53028	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	0,55869	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

23	Kalimantan Timur	32,2305	0,54216	0,58414	-0,04198	0,00176
24	Sulawesi Utara	26,9006	0,44231	0,59950	-0,15719	0,02471
25	Sulawesi Tengah	31,0830	0,52066	0,63472	-0,11406	0,01301
26	Sulawesi Selatan	29,7949	0,49653	0,59996	-0,10343	0,01070
27	Sulawesi Tenggara	29,9012	0,49852	0,59142	-0,09290	0,00863
28	Gorontalo	28,9707	0,48109	0,59517	-0,11408	0,01301
29	Sulawesi Barat	28,2139	0,46691	0,62948	-0,16257	0,02643
30	Maluku	29,0290	0,48218	0,64385	-0,16167	0,02614
31	Maluku Utara	26,2997	0,43105	0,58470	-0,15365	0,02361
32	Papua Barat	24,9856	0,40643	0,54234	-0,13591	0,01847
33	Papua	24,8417	0,40373	0,62311	-0,21938	0,04813
Accuracy						100,00%
MSE						0,016016

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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