International Journal of Engineering and Computer Science Applications (IJECSA)
Vol. 2, No. 1, March 2023, pp. 41∼52
ISSN: 2828-5611
DOI: 10.30812/IJECSA.v2i1.2426

Utilization Of The Conjugate Gradient Algorithm For Predicting School Year Expectations By Province

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Article Info

Article history:

Received October 03, 2022
Revised December 09, 2022
Accepted December 27, 2022

Keywords:

Backpropagation
Cojugate Gradient
Neural Network

ABSTRACT

Expected Length of School (HLS) is the length of school (in years) that is expected to be felt by children at a certain age in the future. It is assumed that the probability that the child will remain in school at the following ages is the same as the probability of the population attending school per total population for the current age. Length of School is also a benchmark for evaluating government programs in improving Human Resources that excel in the competition of technological advances. The purpose of this study is to apply the Conjugate Gradient Algorithm with the Best Performance for Predicting School Life Expectancy in Indonesia. Research data on the Expectation of Schooling in Indonesia consists of 10 Provinces obtained from the Central Statistics Agency from 2016 to 2021. This study uses 5 architectural models, namely 2-10-1, 2-15-1, 2-20-1, 2-25-1 and 2-30-1. Of the five architectural models used, the best architectural model is 2-3-1 with an MSE of 0.000000002 in two seconds. Based on this best architectural model, it will be used to predict the Expectation of Old Schools in Indonesia for the next five years, namely from 2022 to 2026.

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How to Cite: Astri Riamauli Simbolon, and Solikhun, Utilization Of The Conjugate Gradient Algorithm For Predicting School Year Expectations By Province, *International Journal of Engineering and Computer Science Applications (IJECSA)*, vol. 2, no. 1, pp. 41 - 52, March. 2023. doi: 10.30812/ijecsa.v2i2.3406.

1. INTRODUCTION

Expected Length of School (HLS) is the length of school (in years) that is expected to be felt by children at a certain age in the future [1]. HLS can be used to determine the condition of the development of the education system at various levels, which is indicated in the form of the length of education (in years) that is expected to be achieved by each child [2]. The Old School Expectancy Rate is a development method from the old method, namely the Average Length of Schooling and Illiteracy Rate, where the Old School Expectation (HLS) is used and studied as a whole as one indicator of the HDI [3]. However, this paper does not discuss the future results of the Expectation of Old School (HLS) but discusses the ability of the Conjugate Gradient algorithm to make predictions based on the Long-School Expectation (HLS) dataset obtained from the Central Statistics Agency. The conjugate gradient (CG) method is an iterative method to solve the system of linear equations (SPL) in the form of Ax = b, with the coefficient matrix A being positive definite symmetric. This method is widely used to solve large SPL [4]. Backpropagation is one of the algorithms in artificial neural networks that are often used in finding the optimal weight. In the backpropagation network, there is a desired input and output pattern. When the network is given a pattern, the values of the weights are changed in order to minimize the difference between the output pattern of the network and the desired output pattern [5].

In several previous studies on the Expectancy of School Years, such as Arifin M. Kahar's research results, in general, Papua Province holds the most problems in terms of the four predictor variables and HLS numbers compared to the other three provinces [6]. Research on the Effect of Expected Years of Schooling, Average Length of Schooling, and Per Capita Expenditures on the Human Development Index. Policies that can be carried out by the Government are to improve educational infrastructure facilities in 3T (Lagged, Frontier, and Outermost) areas, provide financial assistance for education for underprivileged communities, or conduct training for teaching staff [7]. The Long-School Expectation Rate (HSL) can be increased by providing support to the education sector. The support is in the form of providing outreach programs to the community, namely socialization of 12-year compulsory education, maintenance and addition of mini-village library book collections, and learning assistance activities [8]. Service activities. this has provided changes and community empowerment carried out in every activity, especially in the education and social fields, to improve the quality of education in Sanding Village. For the smoothness and continuation of the programs that have been implemented, cooperation between government agencies and the community is needed [9]. Next is the analysis of the regional Government's strategic planning to increase the expected length of schooling and the average length of schooling.

Based on previous related research, the purpose of this study is to apply the Conjugate Gradient Algorithm with the Best Performance for Predicting School Life Expectancy in Indonesia. The next research is the prediction of the procurement and inventory management of the backpropagation algorithm for artificial neural networks at Perum Bulog. Testing with 15 existing models is obtained. Based on learning from the training data, the best model is obtained with a combination of 12-6-1 (12 input layers, six hidden layers, and one output). layer) combined with 3000 epochs [10]. Furthermore, optimization of the conjugate gradient on the Backpropagation neural network for predicting fish catches proved to use the Conjugate Gradient Backpropagation Neural Network method better with an average MSE value of 0.2223 in 3 stages of testing Cycle Training, Learning Rate, and Hidden Layer [11–15].

2. RESEARCH METHOD

The research framework used to solve this research problem can be seen in Figure 1 [16].

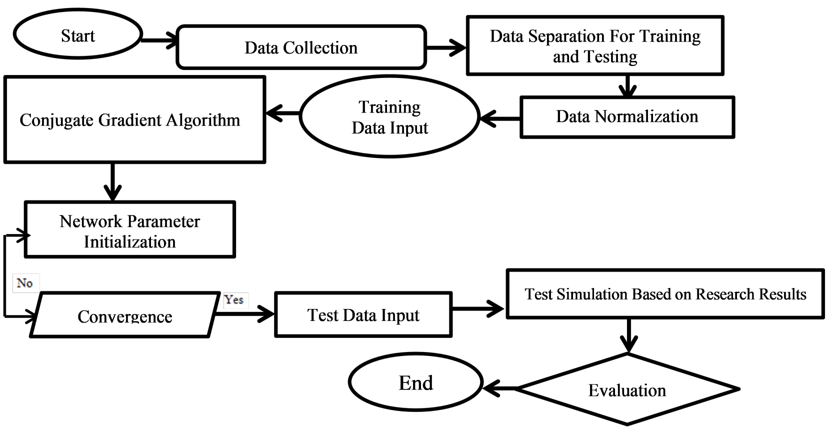

Figure 1. Research Framework

Based on Figure 1, it is explained that collecting data in a study is the first thing that must be done. After that, data separation was carried out for training and testing to be tested on the Conjugate Gradient Algorithm [17]. After that, the data input stage was continued for the normalization process of training data and test data with the equation (1).

$$x' = \frac{0.8(x-a)}{b-a} + 0.1 \tag{1}$$

The explanation for the formula above starts from x', which is the result of data that has been normalized from the original data. 0.8 and 0.1 are the default values for the normalization formula, x is the original data to be normalized, and b is the data with the highest value of all data. Original and a is the data with the lowest or smallest value. The next stage is that the data is distributed for data separation, namely input data, and target data, then the data is ready to be processed in the application of the conjugate gradient algorithm with the type of network function tansig and logsig, after that immediately initialize the network parameters that already selected, namely Trainscg, then enter the command to see the performance results or MSE (Mean Squared Error). If the training data has been processed, then proceed with processing the test data, followed by the last stage, namely conducting an evaluation to see the best architectural model where the assessment is assessed based on the results of the lowest (lowest) performance or MSE [18].

2.1. Data Collection

This study uses the Conjugate Gradient method, which is included in the Artificial Neural Network. This method is used because the Conjugate Gradient can predict using data that has passed (times series). A research dataset is a number of data used at the time of research sourced from the Indonesian Central Statistics Agency for Harapan Lama Schools from 2016-2021 (Table 1) [19].

Table 1. Expected Length of Schooling in Indonesia

Region	Data Expectations of old school					
	2016	2017	2018	2019	2020	2021
Aceh	13.89	14.13	14.27	14.30	14.31	14.36
North Sumatra	13.00	13.10	13.14	13.15	13.23	13.27
West Sumatra	13.79	13.94	13.95	14.01	14.02	14.09
Jambi	12.72	12.87	12.90	12.93	12.98	13.04
Dki Jakarta	12.73	12.86	12.95	12.97	12.98	13.07
West Java	12.30	12.42	12.45	12.48	12.50	12.61
Bali	13.04	13.21	13.23	13.27	13.33	13.40
West Kalimantan	12.37	12.50	12.55	12.58	12.60	12.65
North Sulawesi	12.55	12.66	12.68	12.73	12.85	12.94
Gorontalo	12.88	13.01	13.03	13.06	13.08	13.11

3. RESULT AND ANALYSIS

3.1. Data Normalization Results

Normalization of the data is carried out so that the network output is in accordance with the activation function used [20]. The following table 2 is the result of the normalization of the training data used, namely from 2016 to 2018, with 2018 as the target. This data is taken based on Table 1. These data are normalized using the sigmoid function [21]. The following are the results of the training and testing data for Table 2 (Normalization of Training Data) and Table 3 (Normalization of Testing Data), which are the results of the normalization of the training data used, namely from 2019 to 2021 with 2021 as the target.

Table 2. Normalization of Training Data

Region	2016	2017	2018 (t)
Aceh	0.7457	0.8431	0.9000
North sumatra	0.3843	0.4249	0.4411
West sumatra	0.7051	0.7660	0.7701
Jambi	0.2706	0.3315	0.3437
Dki jakarta	0.2746	0.3274	0.3640
West java	0.1000	0.1487	0.1609
Bali	0.4005	0.4695	0.4777
West kalimantan	0.1284	0.1812	0.2015
North sulawesi	0.2015	0.2462	0.2543
Gorontalo	0.3355	0.3883	0.3964

Table 3. Normalization of Testing Data

Region	2019	2020	2021 (t)
Gorontalo	0.8745	0.8787	0.9000
Aceh	0.3851	0.4191	0.4362
North Sumatra	0.7511	0.7553	0.7851
West Sumatra	0.2915	0.3128	0.3383
Jambi	0.3085	0.3128	0.3511
Dki Jakarta	0.1000	0.1085	0.1553
West Java	0.4362	0.4617	0.4915
Bali	0.1426	0.1511	0.1723
West Kalimantan	0.2064	0.2574	0.2957
North Sulawesi	0.3468	0.3553	0.3681

3.2. Training and Testing

After the normalization phase is complete, the next step is to process the architectural model and train it using the Conjugate Gradient algorithm with the help of the Matlab 2011b application. The architectural models used are 2-10-1, 2-15-1, 2-20-1, 2-25-1, 2-30-1. Then proceed to initialize the Conjugate Gradient algorithm parameters used, which can be seen in the following source code:

```
net.trainParam.epochs            =  10000;
net.trainParam.show              =  25;
net.trainParam.showCommandLine   =  0;
net.trainParam.showWindow        =  1;
net.trainParam.goal              =  0;
net.trainParam.time              =  inf;
net.trainParam.min_grad          =  1e-6;
net.trainParam.max_fail          =  5;
net.trainParam.sigma             =  5.0e-5;
net.trainParam.lambda            =  5.00E-07
```

1. Models 2-10-1

The results of the training using the 2-10-1 architectural model can be seen from the results of the source code that is run on the Matlab 2011b application (Figure 2). The results of the training using this model produce epochs of 622 iterations in 3 seconds. The training and testing table can be seen in Table 3 and Table 5.

Table 4. Training Results Data

No	Training Data					
	X1	X2	Target(Y1)	Epoch 622		
				Actual	Error	Perf
1	0.7457	0.8431	0.9000	0.9000	0.0000	0,000000005
2	0.3843	0.4249	0.4411	0.4411	0.0000	
3	0.7051	0.7660	0.7701	0.7701	0.0000	
4	0.2706	0.3315	0.3437	0.3438	-0.0001	
5	0.2746	0.3274	0.3640	0.3639	0.0001	
6	0.1000	0.1487	0.1609	0.1608	0.0001	
7	0.4005	0.4695	0.4777	0.4777	0.0000	
8	0.1284	0.1812	0.2015	0.2016	-0.0001	
9	0.2015	0.2462	0.2543	0.2543	0.0000	
10	0.3355	0.3883	0.3964	0.3964	0.0000	

Table 5. Test Result Data

No	Testing Data					
	X1	X2	Target(Y1)	Epoch 622		
				Actual	Error	Perf
1	0.8745	0.8787	0.9000	0.8422	0.0578	0,012156932
2	0.3851	0.4191	0.4362	0.4519	-0.0157	
3	0.7511	0.7553	0.7851	0.7274	0.0577	
4	0.2915	0.3128	0.3383	0.4558	-0.1175	
5	0.3085	0.3128	0.3511	0.5252	-0.1741	
6	0.1000	0.1085	0.1553	0.2198	-0.0645	
7	0.4362	0.4617	0.4915	0.6546	-0.1631	
8	0.1426	0.1511	0.1723	0.2808	-0.1085	
9	0.2064	0.2574	0.2957	0.2419	0.053845	
10	0.3468	0.3553	0.3681	0.5265	-0.15841	

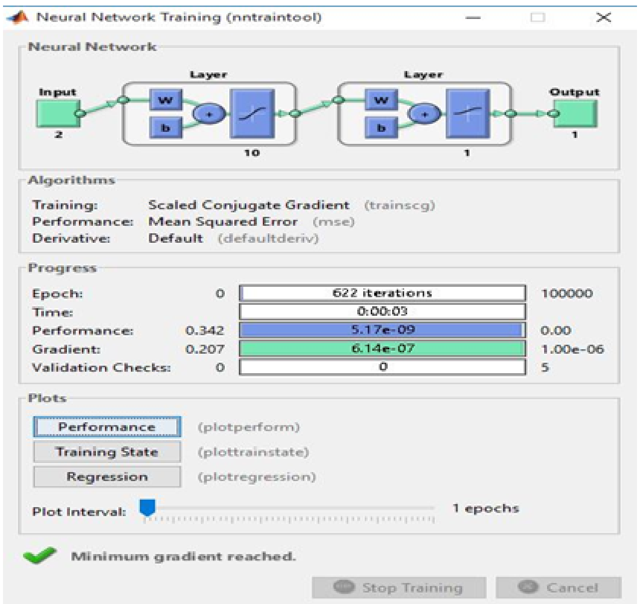

Figure 2. Training Layer 10 with Matlab 2011b

2. Models 2-15-1

The results of the training using the 2-15-1 architectural model can be seen from the results of the source code that is run on the Matlab 2011b application (Figure 3). The results of the training using this model produce epochs of 1469 iterations in 9 seconds. The training and testing table can be seen in Table 6 and Table 7.

Table 6. Training Results Data

No	Training Data					
	X1	X2	Target(Y1)	Epoch 1469		
				Actual	Error	Perf
1	0.7457	0.8431	0.9000	0.9000	0.0000	
2	0.3843	0.4249	0.4411	0.4411	0.0000	
3	0.7051	0.7660	0.7701	0.7701	0.0000	
4	0.2706	0.3315	0.3437	0.3437	0.0000	
5	0.2746	0.3274	0.3640	0.3640	0.0000	0,000000003
6	0.1000	0.1487	0.1609	0.1609	0.0000	
7	0.4005	0.4695	0.4777	0.4777	0.0000	
8	0.1284	0.1812	0.2015	0.2014	0.0001	
9	0.2015	0.2462	0.2543	0.2543	0.0000	
10	0.3355	0.3883	0.3964	0.3964	0.0000	

Table 7. Test Result Data

No	Testing Data					
	X1	X2	Target(Y1)	Epoch 1469		
				Actual	Error	Perf
1	0.8745	0.8787	0.9000	0.8838	0.0162	
2	0.3851	0.4191	0.4362	0.4651	-0.0289	
3	0.7511	0.7553	0.7851	0.7588	0.0263	
4	0.2915	0.3128	0.3383	0.4542	-0.1159	
5	0.3085	0.3128	0.3511	0.5301	-0.1790	0,013968017
6	0.1000	0.1085	0.1553	0.2117	-0.0564	
7	0.4362	0.4617	0.4915	0.6791	-0.1876	
8	0.1426	0.1511	0.1723	0.2739	-0.1016	
9	0.2064	0.2574	0.2957	0.2496	0.0461	
10	0.3468	0.3553	0.3681	0.5720	-0.2039	

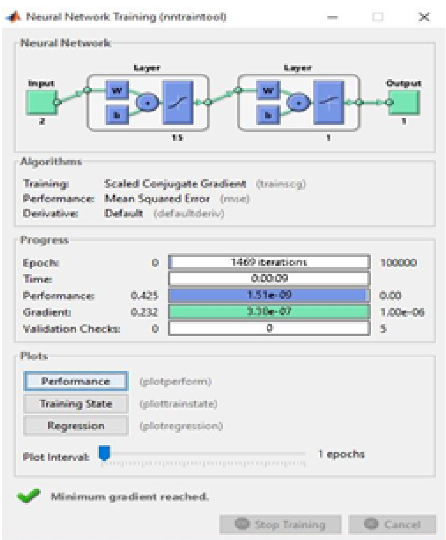

Figure 3. Training Layer 15 with Matlab 2011b

3. Models 2-20-1

The results of the training using the 2-20-1 architectural model can be seen from the results of the source code that is run on the Matlab 2011b application (Figure 4). The results of the training using this model produce epochs of 405 iterations in 3 seconds. The training and testing table can be seen in Table 8 and Table 9.

Table 8. Training Results Data

No	Training Data					
	X1	X2	Target(Y1)	Epoch 405		
				Actual	Error	Perf
1	0.7457	0.8431	0.9000	0.9000	0.0000	0,000000012
2	0.3843	0.4249	0.4411	0.4411	0.0000	
3	0.7051	0.7660	0.7701	0.7701	0.0000	
4	0.2706	0.3315	0.3437	0.3436	0.0001	
5	0.2746	0.3274	0.3640	0.3641	-0.0001	
6	0.1000	0.1487	0.1609	0.1611	-0.0002	
7	0.4005	0.4695	0.4777	0.4777	0.0000	
8	0.1284	0.1812	0.2015	0.2013	0.0002	
9	0.2015	0.2462	0.2543	0.2544	-0.0001	
10	0.3355	0.3883	0.3964	0.3964	0.0000	

Table 9. Test Result Data

No	Testing Data					
	X1	X2	Target(Y1)	Epoch 405		
				Actual	Error	Perf
1	0.8745	0.8787	0.9000	0.8402	0.0598	0,011037398
2	0.3851	0.4191	0.4362	0.4489	-0.0127	
3	0.7511	0.7553	0.7851	0.7262	0.0589	
4	0.2915	0.3128	0.3383	0.4561	-0.1178	
5	0.3085	0.3128	0.3511	0.5213	-0.1702	
6	0.1000	0.1085	0.1553	0.2219	-0.0666	
7	0.4362	0.4617	0.4915	0.6312	-0.1397	
8	0.1426	0.1511	0.1723	0.2832	-0.1109	
9	0.2064	0.2574	0.2957	0.2417	0.0540	
10	0.3468	0.3553	0.3681	0.5135	-0.1454	

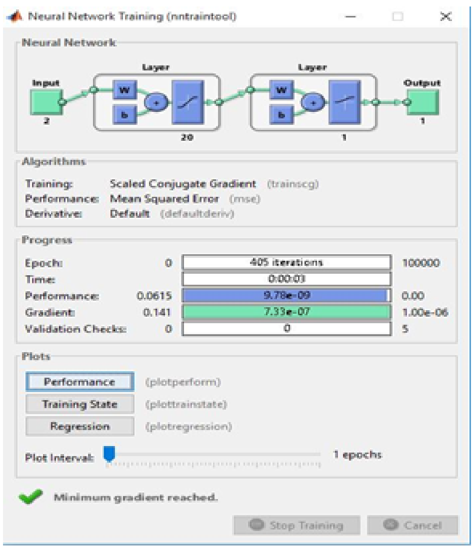

Figure 4. Training Layer 20 with Matlab 2011b

4. Models 2-25-1

The results of the training using the 2-25-1 architectural model can be seen from the results of the source code that is run on the Matlab 2011b application (Figure 5). The results of the training using this model produce epochs of 310 iterations in 2 seconds. The training and testing table can be seen in Table 10 and Table 11.

Table 10. Training Results Data

No	Training Data					
	X1	X2	Target(Y1)	Epoch 310		
				Actual	Error	Perf
1	0.7457	0.8431	0.9000	0.9000	0.0000	
2	0.3843	0.4249	0.4411	0.4411	0.0000	
3	0.7051	0.7660	0.7701	0.7701	0.0000	
4	0.2706	0.3315	0.3437	0.3436	0.0001	
5	0.2746	0.3274	0.3640	0.3641	-0.0001	0,000000003
6	0.1000	0.1487	0.1609	0.1609	0.0000	
7	0.4005	0.4695	0.4777	0.4777	0.0000	
8	0.1284	0.1812	0.2015	0.2015	0.0000	
9	0.2015	0.2462	0.2543	0.2543	0.0000	
10	0.3355	0.3883	0.3964	0.3964	0.0000	

Table 11. Test Result Data

No	Data Testing					
	X1	X2	Target(Y1)	Epoch 310		
				Actual	Error	Perf
1	0.8745	0.8787	0.9000	0.8181	0.0819	
2	0.3851	0.4191	0.4362	0.4528	-0.0166	
3	0.7511	0.7553	0.7851	0.7339	0.0512	
4	0.2915	0.3128	0.3383	0.4787	-0.1404	
5	0.3085	0.3128	0.3511	0.5768	-0.2257	0,012868119
6	0.1000	0.1085	0.1553	0.1242	0.0311	
7	0.4362	0.4617	0.4915	0.5068	-0.0153	
8	0.1426	0.1511	0.1723	0.1373	0.0350	
9	0.2064	0.2574	0.2957	0.2497	0.0460	
10	0.3468	0.3553	0.3681	0.5775	-0.2094	

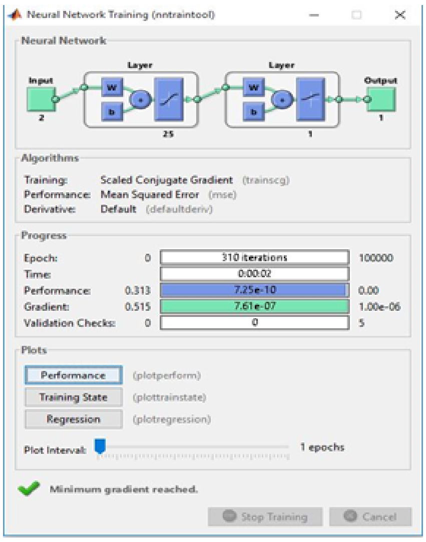

Figure 5. Training Layer 25 with Matlab 2011b

3.3. Models 2-30-1

The results of the training using the 2-30-1 architectural model can be seen from the results of the source code that is run on the Matlab 2011b application (Figure 6). The results of the training using this model produce epochs of 369 iterations in 2 seconds. The training and testing table can be seen in Table 12 and Table 13.

Table 12. Training Results Data

No	Training Data					
	X1	X2	Target(Y1)	Epoch 369		
				Actual	Error	Perf
1	0.7457	0.8431	0,9000	0.9000	0.0000	0,000000002
2	0.3843	0.4249	0.4411	0.4411	0.0000	
3	0.7051	0.7660	0.7701	0.7701	0.0000	
4	0.2706	0.3315	0.3437	0.3437	0.0000	
5	0.2746	0.3274	0.3640	0.3640	0.0000	
6	0.1000	0.1487	0.1609	0.1608	0.0001	
7	0.4005	0.4695	0.4777	0.4777	0.0000	
8	0.1284	0.1812	0.2015	0.2015	0.0000	
9	0.2015	0.2462	0.2543	0.2543	0.0000	
10	0.3355	0.3883	0.3964	0.3964	0.0000	

Table 13. Test Result Data

No	Testing Data					
	X1	X2	Target(Y1)	Epoch 369		
				Actual	Error	Perf
1	0.8745	0.8787	0.9000	0.8472	0.0528	0,004502076
2	0.3851	0.4191	0.4362	0.4196	0.0166	
3	0.7511	0.7553	0.7851	0.6226	0.1625	
4	0.2915	0.3128	0.3383	0.3724	-0.0341	
5	0.3085	0.3128	0.3511	0.3334	0.0177	
6	0.1000	0.1085	0.1553	0.1227	0.0326	
7	0.4362	0.4617	0.4915	0.4214	0.0701	
8	0.1426	0.1511	0.1723	0.1969	-0.0246	
9	0.2064	0.2574	0.2957	0.2441	0.0516	
10	0.3468	0.3553	0.3681	0.2986	0.0694	

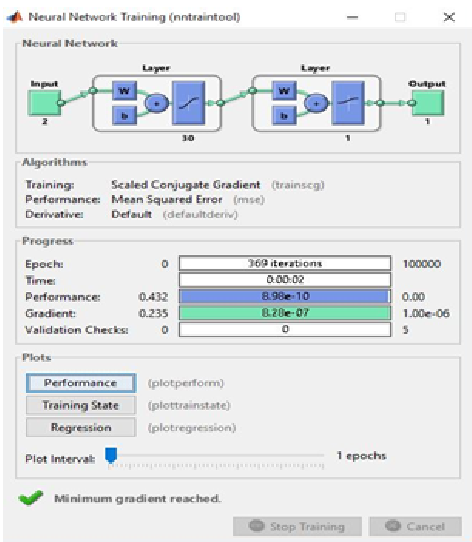

Figure 6. Training Layer 30 with Matlab 2011b

3.4. Evaluation

After training and testing data on architectural models 2-10-1 to 2-30-1 using the help of Matlab 2011b and Microsoft Excel Applications, the best training architecture model is obtained at 2-30-1 with the lowest Performance/MSE test values yaitu 0.000000002 within 2 seconds which is shown in Table 14.

Table 14. Comparison of Overall Model Results

Algoritma	Arsitektur	Fungsi Training	Epoch (Iterasi)	MSE Training	MSE Testing
	2/10/2001	trainscg	622	0.000000005	0.012156932
	2/15/2001	trainscg	1469	0.,000000003	0.013968017
Conjugate Gradient	2/20/2001	trainscg	405	0.000000012	0.011037398
	2/25/2001	trainscg	310	0.000000003	0.012868119
	2-30-1	**trainscg**	**369**	**0.000000002**	**0.004502076**

4. CONCLUSION

Length of School is also a benchmark for evaluating government programs in improving Human Resources that excel in the competition of technological advances. This writing is done to implement and prove that the Backpropagation Algorithm can be used to predict Old School Expectations in Indonesia. The research data is the Expectation of School Years in North Sumatra, which consists of 10 Provinces in Indonesia, and was obtained from the Indonesian Central Statistics Agency from 2016 to 2021. This study uses 5 architectural models, namely 2-10-1, 2-15-1, 2-20-1, 2-25-1 and 2-30-1. Of the five architectural models used, the best architectural model is 2-3-1 with an MSE of 0.000000002. Based on this best architectural model, it will be used to predict the Old School Hope in Indonesia for the next five years, namely from 2022 to 2026.

5. ACKNOWLEDGEMENTS

The Acknowledgments section is optional. Research sources can be included in this section.

6. DECLARATIONS

AUTHOR CONTIBUTION

FUNDING STATEMENT

COMPETING INTEREST

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