



Implementasi algoritma fletcher-reeves dalam menganalisa nilai ekspor menurut golongan sitc

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INFO ARTICLE

Article history:

Received 29 Nov, 2022

Revised 21 Nov 2022

Accepted 30 Nov, 2022

Keywords:

Jaringan Syaraf Tiruan
Fletcher-Reeves
Ekspor

ABSTRACT

Indonesia has a lot of natural resources, so Indonesia uses them by conducting trade activities between countries. Export is a movement to sell or send goods from within the country to abroad. Conjugate gradient Fletcher-Reeves Algorithm According to some references, it is an appropriate development technique compared to the backpropagation strategy because this strategy can speed up the preparation time to arrive at the minimum convergence value. Furthermore, this research shows whether the algorithm performs well and can provide productive assembly results when used to solve problems because the value corresponds to the Standard International Trade Classification (SITC) class. The prediction models used are 5-10-1, 5-15-1, 5-20-1, 5-25-1 and 5-30-1. MSE of 0.00287273, the minimum among the other four models. The model can be used because it produces a fast combination and a fairly short period.

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1. INTRODUCTION

Indonesia has a lot of natural resources, so Indonesia uses them by conducting trade activities between countries (Thoriq, 2022). Export is a movement to sell or send goods from within the country to abroad. With exports, it will provide benefits for foreign workers who can increase state salaries (Wanto & Windarto, 2017). Indonesian salaries account for 42.1% of the country's total revenue. As a result, sending training to a paying country is enormous. However, the long-term value of the product is dubious. This will make it difficult for Indonesia to determine state revenues which will later be used for planning progress programs (Thahara et al., 2021).

Exports are the driving force for economic growth for several reasons, including (1) exports lead to full use of domestic resources according to comparative advantage, (2) exports can expand domestic and foreign markets, and (3) exports are a means to adopt ideas and technology. New ones, (4) exports can encourage the flow of capital from developed countries to developing countries, (5) exports are an effective way to eliminate economic behaviour, and (6) exports generate foreign exchange to provide opportunities for importing capital goods and international goods (Ginantra et al., 2022).

One way to increase exports in Indonesia is to predict or forecast the number of exports according to the central destination countries for the following years (Evanita & Hakim, 2018). Thus, the Government can determine policies by implementing measures that are considered effective in overcoming the decline in the number of petroleum exports in Indonesia. However, the

prediction process is quite tricky. It requires basic models and time series data from these problems, which are generally complicated using estimation accuracy that is not easy to achieve, thus requiring more advanced techniques (Setti et al., 2018).

To help solve this problem, data on the value of exports is needed. From this figure, the public can decide on a strategy to anticipate the riots that will occur (Manurung et al., 2022). Therefore, it is essential to direct researchers to forecast the value of exports in the following several periods using progress and the correct period (Wanto, 2018). Previous researchers said that the Fletcher-Reeves algorithm is one of the techniques commonly used to anticipate artificial neural networks (Sudarsono, 2016) (Edi Ismanto, 2017).

Several related analyses have been carried out, including a study to estimate the value of Oil and Gas and non-oil and gas imports in Indonesia using the Extreme Learning Machine (ELM) strategy (A. B. S. Damanik & Bimantoro, 2018). This experiment was completed by changing the comparison of the number of training data: testing, the number of data included, and hidden neurons with ten trials each. This study obtained results with datasets obtained in general. The smallest average value is 6.6742% for the comparison of the number of training data: testing 70%:30%, the number of information highlights is 5, and the number of secret neurons is 8, while for the dataset that data features, the best results were obtained by comparing how much training information: testing 80%:20%, the number of highlighted information 4, and the number of secret neurons 10 with the last average expected value of 10.0515% (Ramadhani, 2020).

2. RESEARCH METHODOLOGY

2.1 Fletcher-Reeves

E. Stiefel and M.R. Hestenes developed the conjugate gradient algorithm. This method was first used to solve linear or matrix equations iteratively (Hafidz, 2012). According to some references, the Conjugate Gradient Fletcher-Reeves algorithm is a suitable optimization method when juxtaposed with the backpropagation method because this method can speed up the training time to reach the minimum convergence value. The algorithm performs well and can provide efficient convergence results when used to solve problems. Prediction of export value cases according to the Standard International Trade Classification (SITC) (et al., 2017) (Thahara et al., 2021).

2.2 Implementation

Understanding Implementation, according to Kadir, is an activity carried out to test data and apply the system obtained from selection activities. So implementation is a testing process between concept and conceptual or between text and context. According to Fullan, implementation is a process of implementing a new idea, program or set of activities in the hope that others can accept and make changes (Hasanati & Dwiny Meidelfi, 2020). Implementation is a process to assess, evaluate and measure whether a regulation or policy can run well or not, so it will be evaluated whether or not there should be an evaluation of the program (Rahmat, 2017).

2.3 Export & Import

Export is an activity of sending goods or other products from one country to another (Wiko Putra et al., 2019). North Sumatra is one of the provinces in Indonesia, where North Sumatra Province also participates in international trade, especially in exporting (S. M. Damanik et al., 2020). Based on BPS publications on the performance of foreign exchange in 2010, the foreign trade balance of North Sumatra Province reached US\$ 5.57 billion, with export support reaching 9.15 billion and import support at 3.57 billion (Saragih et al., 2018) (Monika et al., 2019).

Import is legally transporting goods or commodities from one country to another. Generally, in the trade process, imports can be defined as the purchase of goods and services from abroad into the country with a cooperation agreement between 2 or more countries (Purba & Wanto, 2018).

2.4 Data

The data used in this study are export value data according to the SITC category from 2010-2020 (Wanto, 2019). The website of the Indonesian Statistics Center is the source of the data to be used, and the data can be seen in the table below:

Table 1. Data Values Exports According to SITC Class

No	Golongan SITC	2010	...	2020
1	Food stuffs and live animals	8276.4	...	14565.1
2	Beverages and tobacco	714.5	...	1243.6
3	Raw ingredients not to be eaten	20270.7	...	14034.4
4	Pelican fuel, polishing material and related materials	46764.8	...	25501.8
5	Fats and animal and vegetable oils	15959.7	...	19709.5
6	Chemicals	8811.9	...	12659.4
7	Manufactured goods are broken down by material	21946.9	...	28591.2
8	Machinery and transportation equipment	19626.4	...	21415.7
9	Various kinds of factory-made goods	14231.2	...	19804.9
10	Items transactions are not specified	1176.6	...	5666.3

2.5 Research Stages

The stages carried out in this research can be seen in the picture below:

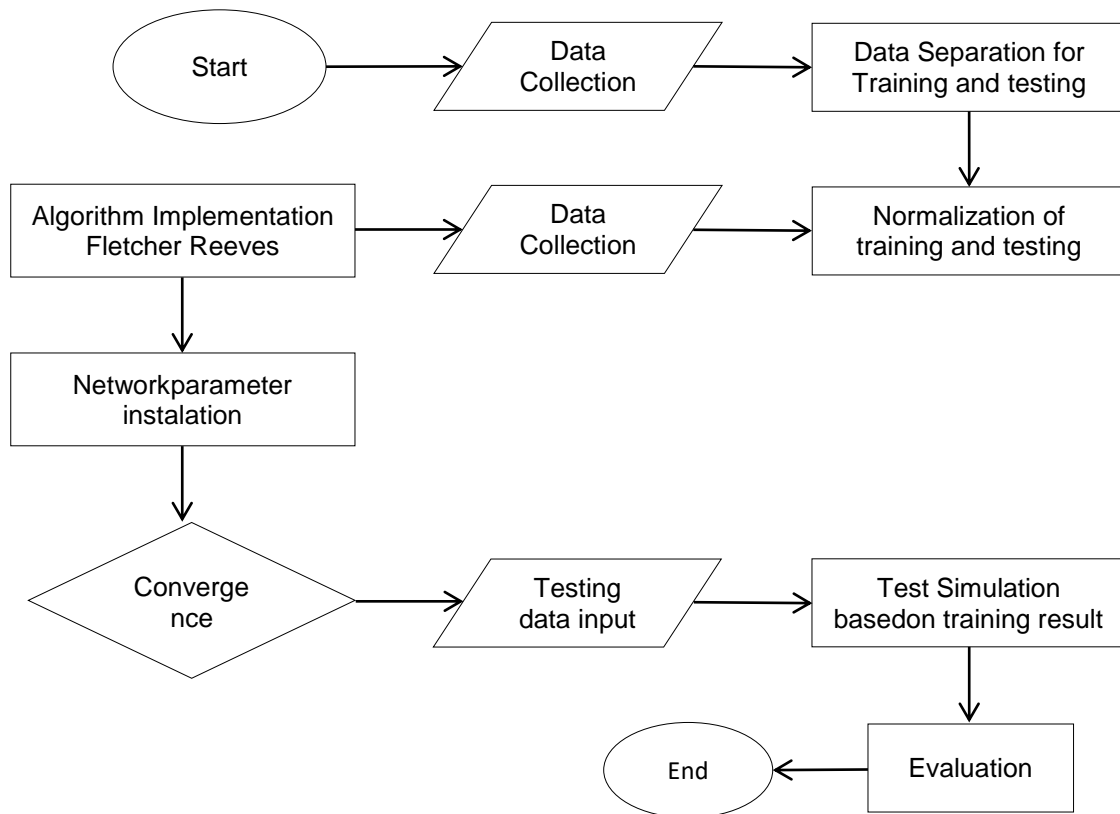


Figure 1: Scheme Preprocessing Data

Scheme Preprocessing Data explains that the first step is to collect data. The data used is export value data by the SITC group. Then the data is divided into two (training data and testing data). Next, determine the architectural model and the method used for the training and testing

process. Finally, after obtaining results based on the methods and models used, select the best model (Saifullah, 2019) (Dewi et al., 2019).

2.6 Normalization

Based on table 1, the data is divided into two. The data for 2010-2015 is for training data and for testing data for 2015-2020. Therefore, there are 2 output variables, namely 2015 for training data and 2020 for testing data. After the data is divided, the data is normalized with the formula below:

$$x' = \frac{0,8(x-b)}{(a-b)} + 0,1 \quad (1)$$

Where x' is the result of normalized data, 0.8 and 0.1 are the fixed values of the normalization formula, x is the data to be normalized, b is the lowest value from the dataset, and a is the highest value from the dataset. The next step is to select the network architecture using the Matlab 2011b application. The next step is to simulate test data based on the training results. The final stage is to evaluate to see the best architectural model based on Performance/MSE testing, where the lowest (small) value is the best (Sinaga et al., 2022).

Description:

x' = Result Normalization

x = Data to be Normalized

a = Smallest Data of the Dataset

b = Biggest Data of Dataset

3. RESULTS AND DISCUSSION

3.1 Data Yield Normalization

The following are normalization results from training data or training data, where X1-X5 is the year 2010-2014 with 2015 as the target (Y1).

Table 2. Results Normalization Data Training

No	X1	X2	X3	X4	X5	Target (Y1)
1	0,1887	0,2103	0,2176	0,2202	0,2332	0,2277
2	0,1000	0,1011	0,1019	0,1036	0,1045	0,1042
3	0,3294	0,3764	0,3125	0,3177	0,2450	0,2414
4	0,6402	0,9000	0,8350	0,7649	0,6907	0,4981
5	0,2788	0,3345	0,3499	0,3092	0,3286	0,3028
6	0,1950	0,2413	0,2159	0,2365	0,2460	0,2095
7	0,3491	0,3906	0,3531	0,3497	0,3577	0,3331
8	0,3218	0,3470	0,3587	0,3513	0,3471	0,3239
9	0,2586	0,2846	0,2853	0,2915	0,3180	0,3313
10	0,1054	0,1177	0,1152	0,1130	0,1096	0,1081

Following are the normalization results from training data or training data, where X6-X10 is the year 2015-2019 with 2020 as the target(y2).

Table 3. Results of Normalization of Test Data

NO	X6	X7	X8	X9	X10	Target (Y2)
1	0,3069	0,3076	0,3310	0,3364	0,3388	0,3651
2	0,1000	0,1013	0,1039	0,1052	0,1050	0,1033
3	0,3298	0,3222	0,3998	0,4253	0,3716	0,3547
4	0,7599	0,6270	0,8037	0,9000	0,7492	0,5801

5	0,4328	0,4226	0,5108	0,4588	0,4087	0,4662
6	0,2763	0,2957	0,3285	0,3587	0,3359	0,3277
7	0,4835	0,4742	0,5183	0,5965	0,5979	0,6408
8	0,4680	0,4890	0,5032	0,5233	0,5357	0,4998
9	0,4804	0,4942	0,4908	0,5027	0,4913	0,4681
10	0,1065	0,1074	0,1169	0,1198	0,1502	0,1902

After the normalization phase is complete, the next step is to determine and train the structural model using the Fletcher-Reeves Algorithm. Each technique consists of 5 models, specifically: 5-15-1 Matlab 2011b. The models used are 5-10-15, 5-15-5, 5-20-5, 5-25-5, and 5-30-5. While the parameters of the Fletcher-Reeves Algorithm used can be seen in Figure 1.

```

% Nilai parameter default Powell-Beale (traincgb)
net.trainParam.epochs = 1000;
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.searchFcn = 'srchcha'
    
```

Figure 1. Parameter Algorithm Fletcher-Reeves

3.2 Model 5-10-1

The training results using the 5-10-1 model resulted in 223 iterations of epochs, which can be seen in the image below.

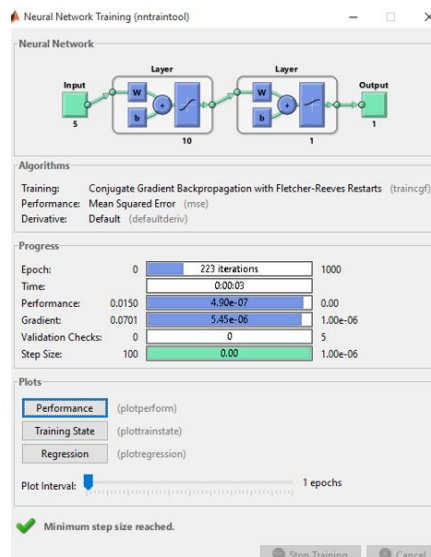


Figure 2. 5-10-1. Model Training

3.3 Model 5-15-1

The training results using the 5-15-1 model resulted in 6 iterations of epochs, which can be seen in the image below.

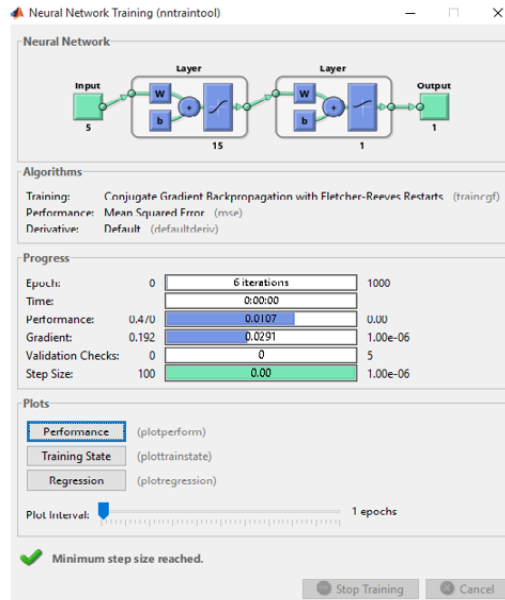


Figure 3. Training Model 5-15-1

3.4 Model 5-20-1

The training results using the 5-20-1 model resulted in 160 iterations of epochs, which can be seen in the image below.

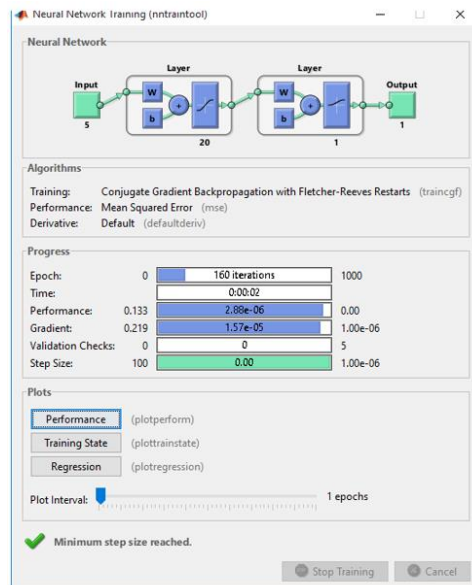


Figure 4. Training Model 5-20-1

3.5 Model 5-25-1

The training results using the 5-25-1 model produce epochs of 358 iterations, which can be seen in the image below.

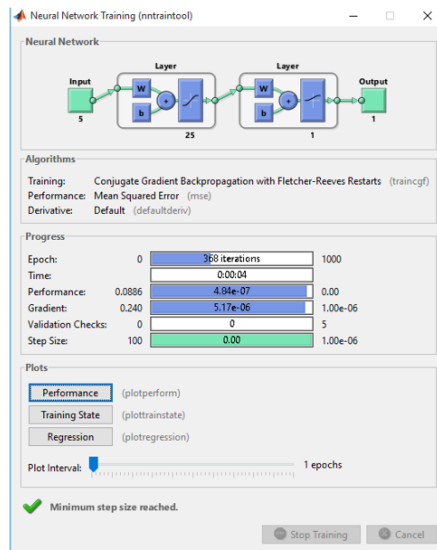


Figure 5. Training Model 5-25-1

3.6 Model 5-30-1

The training results using the 5-30-1 model resulted in 125 iterations of epochs, which can be seen in the image below.

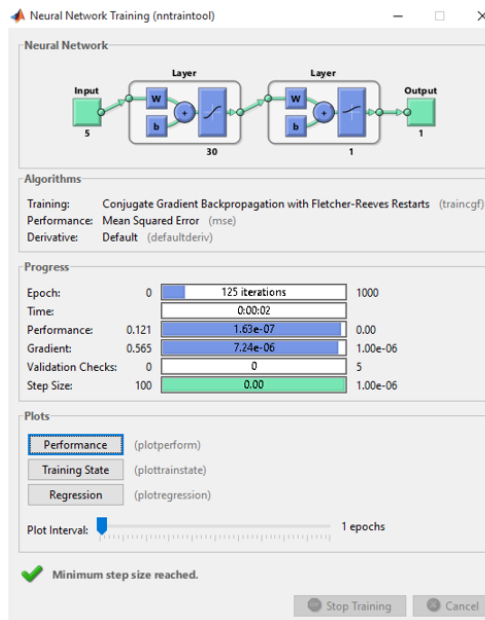


Figure 6. Model 5-30-1. Training

3.7 Analysis and Evaluation

After training and testing data on architectural models 5-10-1, 5-15-1, 5-20-1, 5-25-1 and 5-30-1, it is stated that the 5-25-1 model has the highest value. Low that is 0.00287273, and it is stated that the model is the best.

Tabel 4. Evaluation Model

Architecture	Algorithm	Activation Function	Function Training	Epoch (Iterasi)	MSE Training	MSE Testing/Performance
5-10-1	Fletcher-Reeves	'tansig','logsig'	traincgf	223	0,00000049	0,01423350
5-15-1		'tansig','logsig'	traincgf	6	0,01068004	0,01891732
5-20-1		'tansig','logsig'	traincgf	160	0,00000284	0,02162929
5-25-1		'tansig','logsig'	traincgf	368	0,00000048	0,00287273
5-30-1		'tansig','logsig'	traincgf	125	0,00000017	0,00409739

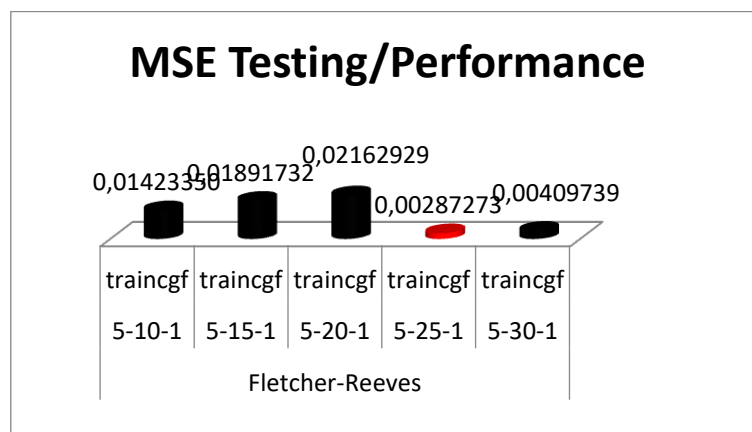


Figure 7. MSE Testing/Performance

4. CONCLUSION

Based on the results and discussion, it can be said that the Conjugate Gradient Fletcher-Reeves Algorithm with a 5-25-1 structure model can be used to predict Export Value according to SITC Group because it doesn't take too long to train to achieve convergence and the resulting performance is quite good compared to the other three structural models. In general, it can be said that the Fletcher-Reeves algorithm (traincgf) can produce a good level of optimization, especially providing a (low) Performance/MSE test value and relatively fast convergence and iteration time.

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