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Performance Analysis and Model Determination for Forecasting Aluminum Imports Using the Powell-Beale Algorithm

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Abstract

Aluminum is one of the most important metals for the industrial world, but currently, aluminum is scarce due to a shortage of electricity, which makes manufacturers limit their production. Therefore, to overcome this scarcity, the government imports aluminum. Imports that are carried out continuously will more or less affect the wheels of the economy in this country. Therefore, it is necessary to predict the value of aluminum imports in the future so that later the demand for aluminum in Indonesia is stable and not too excessive in importing. The prediction method used is the Powell-Beale algorithm, which is one of the most commonly used artificial neural network methods for data prediction. This paper does not discuss the prediction results. Still, it discusses the ability of the Powell-Beale algorithm to make predictions based on imported Aluminum datasets obtained from the Central Statistics Agency. The research data used is aluminum import data by the leading country of origin from 2013-to 2020. A network architecture model will be formed and determined based on this data, including 3-15-1, 3-20-1, and 3-25-1. From these five models, after training and testing, the results show that the best architectural model is 3-20-1 with an MSE value of 0,03010927, the lowest among the other four models. So it can be concluded that the model can be used to predict aluminum imports.

Keywords: *Performance, Forecasting, Imported Aluminum, ANN, Powell-Beale*

1. Introduction

After iron and steel, aluminum is the most widely used non-ferrous metal in the industrial world. Along with time development, aluminum supplies are often scarce, so the government usually imports from foreign countries to meet the need for aluminum. Imports that are carried out continuously will more or less affect the wheels of the economy in this country [1], so it is necessary to anticipate minimizing the increasing dependence on aluminum imports from foreign countries. Therefore, it is essential to forecast the level of aluminum imports in the future so that later the demand for aluminum in Indonesia is stable and not too excessive in importing. The forecasting method proposed in this paper is the Powell-Beale algorithm which is one of the artificial neural network methods that is often used for data forecasting [2]–[4]. However, this paper does not discuss the results of forecasting aluminum imports in the future. Still, it discusses the ability of the Powell-Beale algorithm to forecast based on the aluminum import dataset obtained from the Central Statistics Agency. It is known that Powell-Beale is one of the

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optimization algorithms of conventional backpropagation. So this paper will test it based on architectural models and parameters that have been determined.

Knowing the performance of an artificial neural network algorithm is very important to produce accurate forecasting data. Several studies have been conducted, such as research by Wanto et al. (2017) using backpropagation and Fletcher-Reeves algorithms to solve the problem of forecasting the consumer price index. In this study, the backpropagation algorithm excels in forecasting accuracy by 75% versus 67%, but the Fletcher-Reeves algorithm is much better in terms of performance, MSE and speed [5]. Keshtegar et al. (2019) created a new nonlinear architecture using a modified Fletcher-Reeves conjugate gradient to predict air explosions caused by explosion induction [6]. Timbunan et al. (2020) used the Polak-Ribiere algorithm to improve the performance of the standard backpropagation algorithm in solving population problems. In this study, the Polak-Ribiere algorithm minimized iterations and use time [7].

Based on related descriptions from previous studies, this paper will analyze the performance of the Powell-Beale algorithm to solve the problem of forecasting aluminum imports according to the leading countries of origin such as China, Australia to Japan. This dataset is only used to aid in the verification and process of measuring the algorithm's performance. This research aims to obtain optimization of accuracy and performance measurement of the algorithm in finding the best results to solve the problem of forecasting aluminum imports.

2. Research Methodology

2.1. Data Collection

Data collection in this study uses quantitative methods, namely data on aluminum imports by the top country of origin from 2013-2020, consisting of China, Australia, United Arab Emirates, Malaysia, United States of America, South Korea, Singapore, Qatar, Thailand, and Japan. The data comes from the website of the Indonesian Central Statistics Agency.

Table 1. Aluminum Import Data by Main Country of Origin (Kg)

Country	2013	2014	2015	2016	2017	2018	2019	2020
Tiongkok	141955,1	220461,1	164160,9	156560	233396,2	311145,6	255652,2	204843,5
Australia	121681,2	70508,4	51844,5	66260,6	70439,2	63297,4	43486,4	41117,8
UEA	44436,5	49938,1	38973	55503,5	52322,9	51824,1	52119,6	28042,4
Malaysia,	42282,4	28258,3	35519,6	42835,6	44581,1	52002,6	49742,8	38255,4
USA	30668,9	26550,9	30155,7	23886,4	37406,5	83287,9	105035,3	88325,9
Korea,Selatan	38189,8	33131,3	25573,9	32724,8	33420,3	29535,6	32988,2	25236,2
Singapore	12104,3	17056,1	22788,7	36418,3	29290,9	21014,6	18608,2	24640,3
Qatar	20046,4	17416	28157,4	29424,6	19847,4	16563,7	15150,9	9816,4
Thailand	14517,3	12560,1	14007,3	19351,9	21123,5	17210	15707,4	14965
Japan	10374,7	8547,6	7872,5	7140	6402,8	7763,1	7062,4	6282,5

2.2. Research Flow

Based on figure 1, it can be explained that the first step taken from the research stage is to collect research datasets (Based on table 1). The next step separates the research datasets into two groups: training and testing data. The next step is to normalize the training and testing data using the equation formula (1) [8]–[15].

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

Where: X' is the result of normalized data, 0.8 and 0.1 are the default 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. Furthermore, the normalized training data is entered into the Matlab 2011b application for processing, followed by creating a multi-layer neural network (training data input). Next is the application of the Powell-Beale algorithm. The creation of this multi-layer neural network uses the tansig and logsig functions. The next step is to initialize the network parameters based on the training function (traincgb). Then enter the command to carry out the training process and see the results when performance is found. If the training results reach convergence, it will continue to enter the normalized test data. But if the training results have not reached convergence, return to the initialization stage of network parameters. The next stage is followed by a simulation of test data based on the training results. If everything has been done, the final step is to evaluate to see the best architectural model based on the lowest (small) Performance/MSE test. The stages carried out in this study can be seen in figure 1.

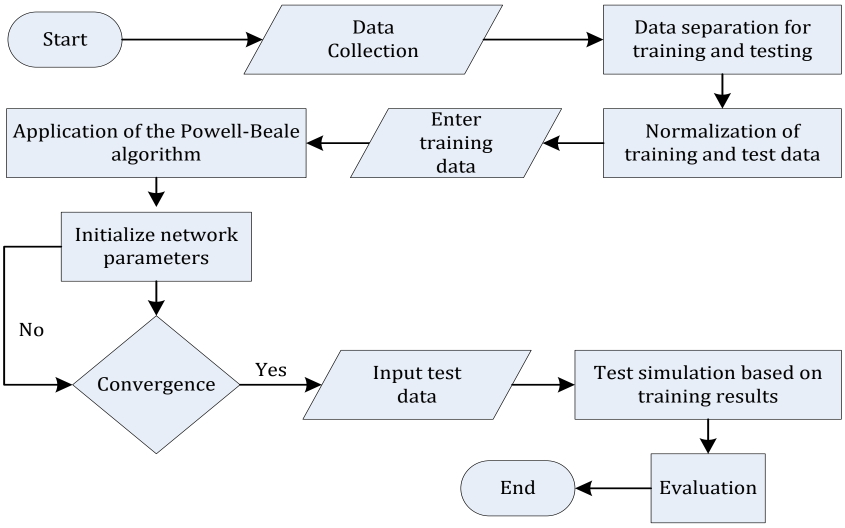

Figure 1. Research Flow

3. Results and Discussion

3.1. Normalizing data

After the research dataset is available, the initial step is to divide the data into two parts (training data and test data). Based on table 1, the training data uses the years 2013-2015 as input and 2016 as the target (output). Meanwhile, the test data use 2017-2019 as input and 2020 as target (work). The data that has been divided into training data and test data is then normalized using equation (1), which has been discussed previously.

Table 2. Training Data

Country	2013 (X1)	2014 (X2)	2015 (X3)	2016 (Target)
Tiongkok	0,4560	0,6620	0,5143	0,4943
Australia	0,4028	0,2685	0,2196	0,2574
UES	0,2001	0,2146	0,1858	0,2292
Malaysia	0,1945	0,1577	0,1767	0,1959
USA	0,1640	0,1532	0,1626	0,1462
South Korea	0,1837	0,1705	0,1506	0,1694
Singapore	0,1153	0,1283	0,1433	0,1791
Qatar	0,1361	0,1292	0,1574	0,1607
Thailand	0,1216	0,1165	0,1203	0,1343
Japan	0,1107	0,1059	0,1042	0,1023

Table 3. Testing Data

Country	2017 (X4)	2018 (X5)	2019 (X6)	2020 (Target)
Tiongkok	0,4560	0,6620	0,5143	0,4943
Australia	0,4028	0,2685	0,2196	0,2574
UES	0,2001	0,2146	0,1858	0,2292
Malaysia	0,1945	0,1577	0,1767	0,1959
USA	0,1640	0,1532	0,1626	0,1462
South Korea	0,1837	0,1705	0,1506	0,1694

Country	2017 (X4)	2018 (X5)	2019 (X6)	2020 (Target)
Singapore	0,1153	0,1283	0,1433	0,1791
Qatar	0,1361	0,1292	0,1574	0,1607
Thailand	0,1216	0,1165	0,1203	0,1343
Japan	0,1107	0,1059	0,1042	0,1023

3.2. Training and Testing Process

After the normalization stage has been completed, the next step is to determine the architectural model and train it using the Powell-Beale algorithm with the help of the Matlab 2011b application. The model used is 3-15-1 (3 inputs, 15 hidden layer neurons, 1 output), 3-20-1 (3 inputs, 20 hidden layer neurons, 1 output), 3-25-1 (3 inputs, 25 hidden layer neurons, 1 output). While the parameters of the Powell-Beale algorithm used can be seen in figure 2.

```
% 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 2. Powell-Beale parameters

a) Model 3-15-1

The results of the training using the 3-15-1 architectural model can be seen in figure 3. The results of the training using this model produce an epoch of 254 iterations.

Table 4. Training Results

Country	X1	X2	X3	Target	Actual	Error	Perf
Tiongkok	0,4560	0,6620	0,5143	0,4943	0,4943	0,0000	0,00003320
Australia	0,4028	0,2685	0,2196	0,2574	0,2574	0,0000	
UEA	0,2001	0,2146	0,1858	0,2292	0,2293	-0,0001	
Malaysia	0,1945	0,1577	0,1767	0,1959	0,1952	0,0007	
USA	0,1640	0,1532	0,1626	0,1462	0,1474	-0,0012	
South Korea	0,1837	0,1705	0,1506	0,1694	0,1696	-0,0002	
Singapore	0,1153	0,1283	0,1433	0,1791	0,1769	0,0022	
Qatar	0,1361	0,1292	0,1574	0,1607	0,1650	-0,0043	
Thailand	0,1216	0,1165	0,1203	0,1343	0,1207	0,0136	
Japan	0,1107	0,1059	0,1042	0,1023	0,1133	-0,0110	

Table 5. Test result

Country	X4	X5	X6	Target	Actual	Error	Perf
Tiongkok	0,6960	0,9000	0,7544	0,6210	0,4638	0,1572	0,03985209
Australia	0,2684	0,2496	0,1976	0,1914	0,3946	-0,2032	
UEA	0,2208	0,2195	0,2203	0,1571	0,2994	-0,1423	
Malaysia	0,2005	0,2200	0,2140	0,1839	0,2568	-0,0729	
USA	0,1817	0,3021	0,3591	0,3153	0,8681	-0,5528	
South Korea	0,1712	0,1610	0,1701	0,1497	0,1590	-0,0093	
Singapore	0,1604	0,1387	0,1323	0,1482	0,1244	0,0238	
Qatar	0,1356	0,1270	0,1233	0,1093	0,1125	-0,0032	
Thailand	0,1389	0,1287	0,1247	0,1228	0,1127	0,0101	
Japan	0,1003	0,1039	0,1020	0,1000	0,1242	-0,0242	

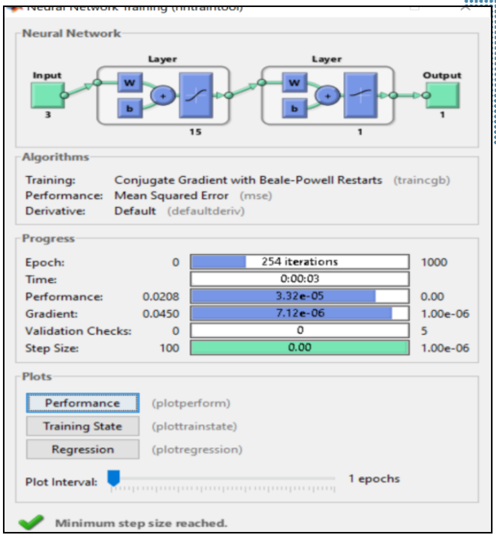

Figure 3. Training with Matlab (Model 3-15-1)

b) Model 3-20-1

The results of the training using the 3-20-1 architectural model can be seen in figure 4. The results of the training using this model produce epochs of 5 iterations.

Table 6. Training Results

Country	X1	X2	X3	Target	Actual	Error	Perf
Tiongkok	0,4560	0,6620	0,5143	0,4943	0,4945	-0,0002	0,022727648
Australia	0,4028	0,2685	0,2196	0,2574	0,2590	-0,0016	
UEA	0,2001	0,2146	0,1858	0,2292	0,0001	0,2291	
Malaysia	0,1945	0,1577	0,1767	0,1959	0,0001	0,1958	
USA	0,1640	0,1532	0,1626	0,1462	0,0000	0,1462	
South Korea	0,1837	0,1705	0,1506	0,1694	0,0000	0,1694	
Singapore	0,1153	0,1283	0,1433	0,1791	0,0000	0,1791	
Qatar	0,1361	0,1292	0,1574	0,1607	0,0000	0,1607	
Thailand	0,1216	0,1165	0,1203	0,1343	0,0000	0,1343	
Japan	0,1107	0,1059	0,1042	0,1023	0,0000	0,1023	

Table 7. Test result

Country	X4	X5	X6	Target	Actual	Error	Perf
Tiongkok	0,6960	0,9000	0,7544	0,6210	0,7883	-0,1673	0,03010927
Australia	0,2684	0,2496	0,1976	0,1914	0,0031	0,1883	
UEA	0,2208	0,2195	0,2203	0,1571	0,0004	0,1567	
Malaysia	0,2005	0,2200	0,2140	0,1839	0,0002	0,1837	
USA	0,1817	0,3021	0,3591	0,3153	0,0023	0,3130	
South Korea	0,1712	0,1610	0,1701	0,1497	0,0000	0,1497	
Singapore	0,1604	0,1387	0,1323	0,1482	0,0000	0,1482	
Qatar	0,1356	0,1270	0,1233	0,1093	0,0000	0,1093	
Thailand	0,1389	0,1287	0,1247	0,1228	0,0000	0,1228	
Japan	0,1003	0,1039	0,1020	0,1000	0,0000	0,1000	

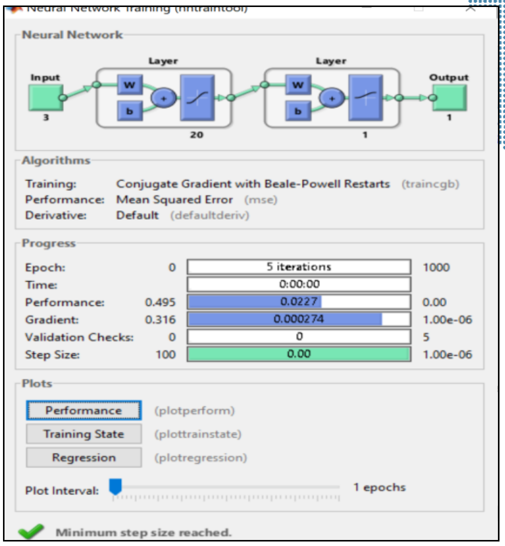

Figure 4. Training with Matlab (3-20-1)

c) Model 3-25-1

The results of the training using the 3-25-1 architectural model can be seen in figure 5. The results of the training using this model produce 52 iterations of epochs.

Table 8. Training Results

Country	X1	X2	X3	Target	Actual	Error	Perf
Tiongkok	0,4560	0,6620	0,5143	0,4943	0,0000	0,4943	0,03109614
Australia	0,4028	0,2685	0,2196	0,2574	0,0000	0,2574	
UEA	0,2001	0,2146	0,1858	0,2292	0,2333	-0,0041	
Malaysia	0,1945	0,1577	0,1767	0,1959	0,1917	0,0042	
USA	0,1640	0,1532	0,1626	0,1462	0,1556	-0,0094	
South Korea	0,1837	0,1705	0,1506	0,1694	0,1663	0,0031	
Singapore	0,1153	0,1283	0,1433	0,1791	0,1752	0,0039	
Qatar	0,1361	0,1292	0,1574	0,1607	0,1587	0,0020	
Thailand	0,1216	0,1165	0,1203	0,1343	0,1260	0,0083	
Japan	0,1107	0,1059	0,1042	0,1023	0,1128	-0,0105	

Table 9. Testing Results

Country	X4	X5	X6	Target	Actual	Error	Perf
Tiongkok	0,6960	0,9000	0,7544	0,6210	0,0000	0,6210	0,066538109
Australia	0,2684	0,2496	0,1976	0,1914	0,6853	-0,4939	
UEA	0,2208	0,2195	0,2203	0,1571	0,2425	-0,0854	
Malaysia	0,2005	0,2200	0,2140	0,1839	0,2171	-0,0332	
USA	0,1817	0,3021	0,3591	0,3153	0,1544	0,1609	
South Korea	0,1712	0,1610	0,1701	0,1497	0,1636	-0,0139	
Singapore	0,1604	0,1387	0,1323	0,1482	0,1239	0,0243	
Qatar	0,1356	0,1270	0,1233	0,1093	0,1206	-0,0113	
Thailand	0,1389	0,1287	0,1247	0,1228	0,1205	0,0023	
Japan	0,1003	0,1039	0,1020	0,1000	0,1236	-0,0236	

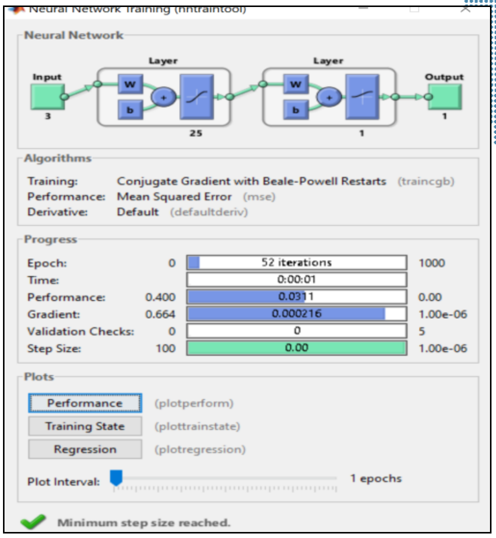

Figure 5. Training with Matlab (3-25-1)

3.4. Evaluation

After training and testing data on architectural models 3-15-1, 3-20-1 and 3-25-1 using Matlab and Microsoft Excel tools, the best architectural model is 3-20-1 with Performance/MSE testing values. the lowest is 0.03010927.

Table 10. Overall Model Comparison

Algorithm	Model	Epoch (Iteration)	MSE Testing / Performance
Powell-Beale	3-15-1	254	0,03985209
	3-20-1	5	0,03010927
	3-25-1	52	0,06653811

4. Conclusion

Based on the results and discussion, it can be concluded that the Powell-Beale Conjugate Gradient Algorithm with architectural model 3-20-1 can be used and utilized to predict aluminum imports in Indonesia according to the leading country of origin because the training time for achieving convergence is not too long and performance The resulting model is quite good compared to the other four architectural models. Overall it can also be concluded that the Powell-Beale algorithm (traincgb) can produce a good level of optimization, namely making a (low) Performance/ MSE test value, time to achieve convergence, and relatively fast iteration.

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