International Journal of Engineering and Computer Science Applications (IJECSA)
Vol. 2, No. 1, March 2023, pp. 29~38
ISSN:2828-5611
DOI: 10.30812/IJECSA.v2i1.2420

Performance Machine Learning Powel-Beale for Predicting Rubber Plant Production in Sumatra

Siska Rama Dani[1], Solikhun[2], Dadang Priyanto[3]
[1, 2]STIKOM Tunas Bangsa, Pematang Siantar, Indonesia
[3]Universitas Bumigora, Mataram, Indonesia

Article Info

Article history:

Received October 1, 2022
Revised December 8, 2022
Accepted January 24, 2023

Keywords:

Artificial Neural Network
Machine Learning
Prediction
Rubber Plant Production

ABSTRACT

This study aims to predict rubber plants in Sumatra; rubber plants have a relatively high economic value; rubber sap must be cultivated because it is a product of the rubber plant, which is the raw material for the rubber industry, so in large quantities. Therefore, rubber sap, the selling value will increase so that it can increase farmers' income. Rubber production in Sumatra experiences ups and downs; therefore, this study aims to predict rubber plants using the Powell-Beale algorithm method, one of the Artificial Neural Network methods often used for data prediction, implemented using Matlab software. That supports it. This study does not discuss the prediction results. Still, it discusses the ability of the Powell-Beale algorithm to make predictions based on datasets of rubber plant production in recent years obtained from the Central Statistics Agency. Based on this data, a network architecture model will be formed and determined, including 6-10-1, 6-15-1, 6-30-1, 6-45-1 and 6-50-1. The best architecture is 6-15-1, with the lowest Performance/MSE test score of 0.00791984.

Corresponding Author:

Solikhun,
STIKOM Tunas Bangsa, Pematang Siantar, Indonesia.
Email: solikhun@amiktunasbangsa.ac.id

1 INTRODUCTION

Rubber (Hevea brasiliensis) belongs to the genus Hevea of the family Euphorbiaceae, a tropical woody tree from the Amazon forest[1]. Rubber occupies the third largest plantation area after oil palm and coconut[2]. Rubber plants are one of the critical agricultural commodities for Indonesian plantations and internationally[3]. Indonesia is still faced with the reality of the low quality of rubber processing materials, limited access to finished goods marketing, minimal financing capabilities, and simple mastery of technology as weaknesses [4]. Attention to the growing conditions and the ideal environment for this plant if you want your rubber plant to grow well and produce a lot of sap[5]. Rainfall also affects groundwater availability because, during the dry season, the rain decreases, so it becomes a limiting factor for the growth of rubber plants[6]. With a land area of 585,749.21 hectares, North Sumatra Province produced 547,300.83 tons of rubber in 2019[7]. According to information from the North Sumatra Plantation Service, smallholder plantations with a land area of 393,189.02 ha produced the most rubber, up to 311,076.66 tons. This achievement represents approximately 56.83 per cent of the total production of North Sumatra. Manufacturing PT is ongoing (Produksi Karet Menurut Provinsi Di Indonesia , 2008 - 2012 Rubber Production by Province in Indonesia , 2008 - 2012, 2012).

The importance of natural rubber commodities causes proper handling in developing export competitiveness so that this commodity can be used as one of the pillars of the national economy[8]. BPS data (2014) states that in 2013 Indonesia's natural rubber export volume reached 2 590 200 tons with a total export value of US$ 6.6 billion [9]. The volume of rubber exports is not influenced by the amount of rubber production but also by the price of rubber itself, where the prevailing price is the average price of rubber on the world market [10]. Fluctuating rubber prices and tends to decline, simple management techniques cause the contribution of rubber plantations to people's incomes and the economy to decline Production on natural rubber plantations is rural development in Indonesia[11].

Fresh, natural rubber latex obtained from exploiting the Hevea brasiliensis tree is a white colloid composed of a long-chain cis-1,4 polyisoprene biopolymer and several non-polyisoprene components such as proteins, fats and carbohydrates [12]. Rubber latex production is expected to remain stable or increase, given the great demand for rubber in the community. In North Sumatra, rubber is one of the plantation products that play an essential role [13]. The high level of natural rubber production in Indonesia while domestic demand is still low makes Indonesia prefer to export activities to other countries [14]. Rubber farming productivity is still being worked on, especially in cultivation technology [15]. Farmers began to replace rubber crops with other crops with higher economic value due to the problem of rubber prices which have yet to bring good news to farmers. However, farmers are still optimistic because several sectors rely on their products [16].

Backpropagation Neural Networks are a helpful tool for prediction because the backpropagation algorithm allows the avoidance of challenges to explain the use of learning principles analogous to the time-dependent plasticity of synaptic spikes [17]. Machine Learning offers an alternative approach to standard modelling that might overcome current limitations [18].Backpropagation is a supervised training method in the sense that it has a target to look for [19]. The Backpropagation algorithm, however, tends to achieve convergence to get the best accuracy [20]. As a result, different techniques for optimization are required. For example, conjugate Gradient is a search algorithm whose search direction does not always decrease but is based on the order of the conjunction [21]. The Conjugate Gradient Beale Powell Restart optimization technique will be applied. The unconstrained optimization problem is often solved using this technique [22]. We will learn how rubber develops in North Sumatra using this strategy. The world's largest natural rubber producer could finally be Indonesia[23]. According to an IRSG assessment from 2007, 13 million tonnes of natural rubber will be produced globally by 2020.

Based on previous research[24] Rubber is a commodity for producing tires, balloons and other rubber products. Indonesia is the second largest rubber producer and distributor in the world. However, the level of rubber production tends to fluctuate. Thus, an analysis is needed to predict rubber production in the future so that rubber plantations, especially those owned by the people, can take precautions if there is a decline in production. One way that can be done to predict is to utilize an Artificial Neural Network with the Backpropagation method, because it can provide accurate results. In this study, 10 network architecture models were tested and the best architecture was obtained, namely 10-10-11-1 with an accuracy of 96%. With this architecture, predictions were made and estimates of rubber production in North Sumatra for 2021-2025 were obtained. This study aims to predict rubber factory production using the Powell-Beale algorithm method, one of the Artificial Neural Network methods that is often used for data prediction, implemented using Matlab software.

2 RESEARCH METHOD

2.1. Data Collection

A quantitative approach was used to obtain data in this study, namely information on Sumatran rubber production from 2009 to 2020. The announcement was obtained from the website of the Indonesian Central Statistics Agency. The data can be seen in the Table 1.

Table 1. Rubber Plant Production in Sumatra(Tons)

Province	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Aceh	80.90	93.10	106.40	107.45	74.79	74.50	74.80	83.10	98.20	93.70	85.20	74.80

Sumatera Utara	382.10	430.10	481.40	486.31	448.97	409.50	409.80	413.30	460.90	418.90	387.70	327.70
Sumatera Barat	85.00	95.10	105.00	107.04	120.98	120.60	120.00	135.90	152.40	152.50	142.00	132.10
Riau	325.10	365.10	396.20	398.92	324.21	323.60	322.50	336.70	368.60	337.30	308.00	291.90
Jambi	273.20	306.30	319.90	322.38	270.25	262.20	260.60	283.10	315.40	319.50	301.40	262.80
Sumatera Selatan	484.00	537.90	567.30	569.17	932.50	947.90	944.00	960.00	1035.50	1043.00	944.20	804.80
Bengkulu	46.20	51.40	62.10	62.59	93.33	92.50	95.80	106.80	122.40	126.30	113.60	94.10
Lampung	62.10	67.90	77.00	77.49	66.86	130.60	130.20	155.40	159.80	174.10	148.50	136.90
Kep. Bangka Belitung	17.70	19.80	23.30	24.02	41.15	46.20	45.90	52.70	59.40	59.90	55.10	46.50
Kep. Riau	19.90	22.30	27.60	27.59	20.16	20.80	20.70	22.90	30.20	29.40	23.30	19.00

2.2. Research Flow

The stages of this research are shown in Figure 1.

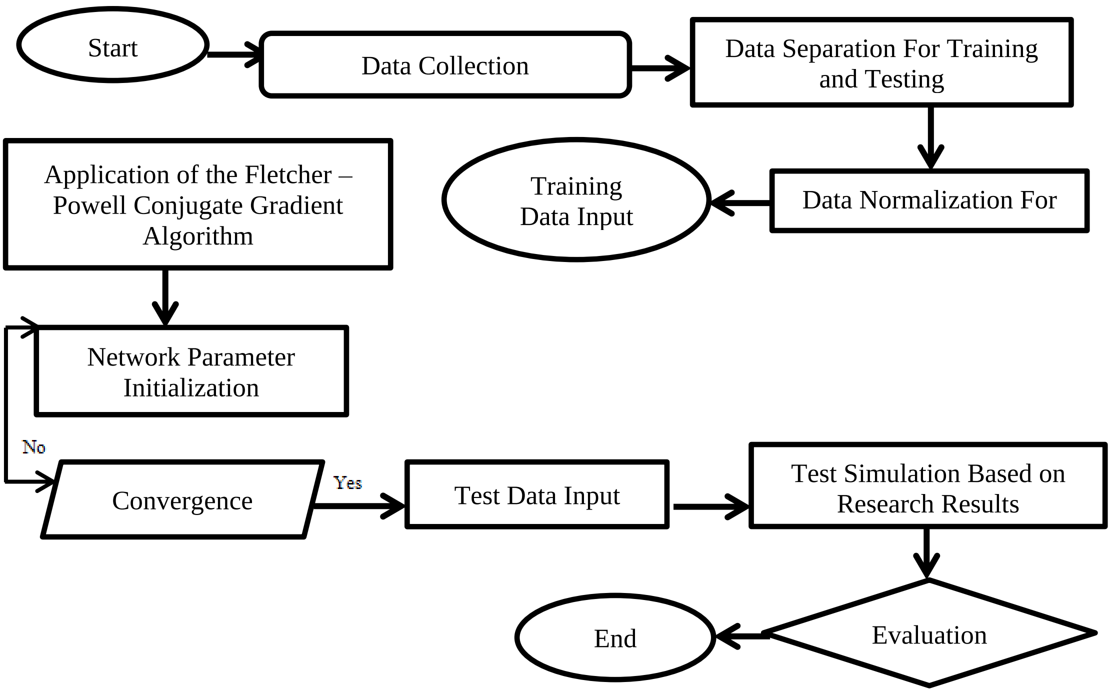

Figure 1. Research Stages

Figure 1 illustrates that the collection of research datasets is the first action taken during the research phase (Based on Table 1). The research dataset is divided into training and testing data groups in the following stages. The training and test data were then normalized using the following mathematical formula (1).

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

Where: X' is the output of the normalization process, 0.8 and 0.1 are the default values of the normalization formula, X is the data that must be normalized, b is the lowest value of the dataset, and an is the largest value. In addition, a multi-layer neural network was created after processing the normalized training data in the Matlab 2011b application (training data input). The application of the Powell-Beale algorithm comes next. The tansig and logsig functions are used to build this multi-layer neural network. Initialization of network parameters depending on the training function used is the following step (traincgb). Once the performance is determined, enter the command to start the training process and see the results.

2.3. Findings and Discussion

Separation of Data between Training and Testing

After the research dataset is obtained, the first thing to do is to divide it into two parts (training data and test data). Table 1 provides input and target year for training data, namely 2009 to 2013. (output). Test data is input from 2015 to 2019 with a target of 2020 (output).

2.4. Normalization Results

The previously described formula (1) was then used to normalize the data after it was broken down into training (Shown Table 2) and test sets (Shown Table 3).

Table 2. Training Data

2009	2010	2011	2012	2013	2014 (T)
0,1325	0,1430	0,1544	0,1553	0,1272	0,1270
0,3915	0,4328	0,4769	0,4811	0,4490	0,4151
0,1360	0,1447	0,1532	0,1549	0,1669	0,1666
0,3425	0,3769	0,4036	0,4060	0,3417	0,3412
0,2978	0,3263	0,3380	0,3401	0,2953	0,2884
0,4791	0,5255	0,5508	0,5524	0,8649	0,8781
0,10 26	0,1071	0,1163	0,1167	0,1432	0,1424
0,1163	0,1213	0,1291	0,1295	0,1204	0,1752
0,0781	0,0799	0,0829	0,0835	0,0983	0,1026
0,0800	0,0821	0,0866	0,0866	0,0802	0,0808

Table 3. Test Data

2015	2016	2017	2018	2019	2020 (T)
0,1223	0,1288	0,1405	0,1370	0,1304	0,1223
0,3840	0,3867	0,4239	0,3911	0,3667	0,3198
0,1576	0,1700	0,1829	0,1830	0,1748	0,1670
0,3158	0,3269	0,3518	0,3273	0,3045	0,2919
0,2674	0,2850	0,3102	0,3134	0,2993	0,2691
0,8013	0,8138	0,8728	0,8787	0,8015	0,6926
0,1387	0,1473	0,1595	0,1625	0,1526	0,1373
0,1655	0,1852	0,1887	0,1998	0,1798	0,1708
0,0997	0,1050	0,1102	0,1106	0,1069	0,1002
0,0800	0,0817	0,0874	0,0868	0,0820	0,0787

2.5. Testing and Training

After the normalization stage, the architectural model must be determined and trained using the Powell-Beale algorithm with the help of the Matlab 2011b application. The model used has five inputs, ten hidden layer neurons, one output, five inputs, fifteen hidden layer neurons, one output, five inputs, thirty hidden layer neurons, five inputs, forty five hidden layer neurons, and five inputs, fifty neurons (5 inputs, 50 hidden layer neurons, 1 output). The Figure 2 the Powell-Beale algorithm setup.

```
% 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 Algorithm

a. Models 6-10-1

40 iteration epochs were generated as a result of training with the 6-10-1 model. The Table 4 shows the training and the Table 5 shown testing schedule.

Table 4. Training Data Model 6-10-1

X1	X2	X3	X4	X5	Target (Y1)	Epoch 40		
						Actual	**Error**	**Perf**
0,1325	0,1430	0,1544	0,1553	0,1272	0,1270	0,1438	-0,0168	
0,3915	0,4328	0,4769	0,4811	0,4490	0,4151	0,5441	-0,1290	
0,1360	0,1447	0,1532	0,1549	0,1669	0,1666	0,1522	0,0144	
0,3425	0,3769	0,4036	0,4060	0,3417	0,3412	0,3765	-0,0353	
0,2978	0,3263	0,3380	0,3401	0,2953	0,2884	0,2753	0,0131	0,0042
0,4791	0,5255	0,5508	0,5524	0,8649	0,8781	0,7435	0,1346	
0,1026	0,1071	0,1163	0,1167	0,1432	0,1424	0,1017	0,0407	
0,1163	0,1213	0,1291	0,1295	0,1204	0,1752	0,1182	0,0570	
0,0781	0,0799	0,0829	0,0835	0,0983	0,1026	0,0790	0,0236	
0,0800	0,0821	0,0866	0,0866	0,0802	0,0808	0,0800	0,0008	

Table 5. Model Test Data 6-10-1

X1	X2	X3	X4	X5	Target (Y1)	Epoch 40		
						Actual	**Error**	**Perf**
0,1223	0,1288	0,1405	0,1370	0,1304	0,1223	0,127	-0,0047	
0,3840	0,3867	0,4239	0,3911	0,3667	0,3198	0,3546	-0,0348	
0,1576	0,1700	0,1829	0,1830	0,1748	0,1670	0,1771	-0,0101	
0,3158	0,3269	0,3518	0,3273	0,3045	0,2919	0,2803	0,0116	
0,2674	0,2850	0,3102	0,3134	0,2993	0,2691	0,2476	0,0215	0,00227787
0,8013	0,8138	0,8728	0,8787	0,8015	0,6926	0,8353	-0,1427	
0,1387	0,1473	0,1595	0,1625	0,1526	0,1373	0,1532	-0,0159	
0,1655	0,1852	0,1887	0,1998	0,1798	0,1708	0,1853	-0,0145	
0,0997	0,1050	0,1102	0,1106	0,1069	0,1002	0,0962	0,0040	
0,0800	0,0817	0,0874	0,0868	0,0820	0,0787	0,0799	-0,0012	

b. Models 6-15-1

The results of this model training produce epochs with 213 iterations. The Table 6 shows the training and Table 7 shown testing schedule.

Table 6. Model Training Data 6-15-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 213		
							Actual	Error	Perf
1	0,1325	0,1430	0,1544	0,1553	0,1272	0,1270	0,1265	0,0005	0,00000010
2	0,3915	0,4328	0,4769	0,4811	0,4490	0,4151	0,4151	0,0000	
3	0,1360	0,1447	0,1532	0,1549	0,1669	0,1666	0,1669	-0,0003	
4	0,3425	0,3769	0,4036	0,4060	0,3417	0,3412	0,3410	0,0002	
5	0,2978	0,3263	0,3380	0,3401	0,2953	0,2884	0,2886	-0,0002	
6	0,4791	0,5255	0,5508	0,5524	0,8649	0,8781	0,8781	0,0000	
7	0,1026	0,1071	0,1163	0,1167	0,1432	0,1424	0,1421	0,0003	
8	0,1163	0,1213	0,1291	0,1295	0,1204	0,1752	0,1754	-0,0002	
9	0,0781	0,0799	0,0829	0,0835	0,0983	0,1026	0,1023	0,0003	
10	0,0800	0,0821	0,0866	0,0866	0,0802	0,0808	0,0814	-0,0006	

Table 7. Model Test Data 6-15-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 213		
							Actual	Error	Perf
1	0,1223	0,1288	0,1405	0,1370	0,1304	0,1223	0,1136	0,0087	0,00791984
2	0,3840	0,3867	0,4239	0,3911	0,3667	0,3198	0,2973	0,0225	
3	0,1576	0,1700	0,1829	0,1830	0,1748	0,1670	0,1843	-0,0173	
4	0,3158	0,3269	0,3518	0,3273	0,3045	0,2919	0,2765	0,0154	
5	0,2674	0,2850	0,3102	0,3134	0,2993	0,2691	0,3017	-0,0326	
6	0,8013	0,8138	0,8728	0,8787	0,8015	0,6926	0,9681	-0,2755	
7	0,1387	0,1473	0,1595	0,1625	0,1526	0,1373	0,1426	-0,0053	
8	0,1655	0,1852	0,1887	0,1998	0,1798	0,1708	0,2028	-0,0320	
9	0,0997	0,1050	0,1102	0,1106	0,1069	0,1002	0,0931	0,0071	
10	0,0800	0,0817	0,0874	0,0868	0,0820	0,0787	0,0810	-0,0023	

c. Models 6-30-1

An epoch with 276 iterations was generated as a result of training with this model. The Table 8 shows the training and the Table 9 shown testing schedule.

Table 8. Training Data 6-30-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 276		
							Actual	Error	Perf
1	0,1325	0,1430	0,1544	0,1553	0,1272	0,1270	0,1341	-0,0071	0,00034630
2	0,3915	0,4328	0,4769	0,4811	0,4490	0,4151	0,4217	-0,0066	
3	0,1360	0,1447	0,1532	0,1549	0,1669	0,1666	0,1652	0,0014	
4	0,3425	0,3769	0,4036	0,4060	0,3417	0,3412	0,3248	0,0164	
5	0,2978	0,3263	0,3380	0,3401	0,2953	0,2884	0,2512	0,0372	
6	0,4791	0,5255	0,5508	0,5524	0,8649	0,8781	0,8833	-0,0052	
7	0,1026	0,1071	0,1163	0,1167	0,1432	0,1424	0,1403	0,0021	
8	0,1163	0,1213	0,1291	0,1295	0,1204	0,1752	0,1365	0,0387	
9	0,0781	0,0799	0,0829	0,0835	0,0983	0,1026	0,1048	-0,0022	
10	0,0800	0,0821	0,0866	0,0866	0,0802	0,0808	0,0942	-0,0134	

Table 9. Test Data Model 6-30-1

No	X1	X2	X3	X4	X5	Target	Epoch 276

						(Y1)	Actual	Error	Perf
1	0,1223	0,1288	0,1405	0,1370	0,1304	0,1223	0,1297	-0,0074	
2	0,3840	0,3867	0,4239	0,3911	0,3667	0,3198	0,3315	-0,0117	
3	0,1576	0,1700	0,1829	0,1830	0,1748	0,1670	0,1699	-0,0029	
4	0,3158	0,3269	0,3518	0,3273	0,3045	0,2919	0,2603	0,0316	
5	0,2674	0,2850	0,3102	0,3134	0,2993	0,2691	0,2427	0,0264	0,00055285
6	0,8013	0,8138	0,8728	0,8787	0,8015	0,6926	0,7487	-0,0561	
7	0,1387	0,1473	0,1595	0,1625	0,1526	0,1373	0,1479	-0,0106	
8	0,1655	0,1852	0,1887	0,1998	0,1798	0,1708	0,1739	-0,0031	
9	0,0997	0,1050	0,1102	0,1106	0,1069	0,1002	0,1101	-0,0099	
10	0,0800	0,0817	0,0874	0,0868	0,0820	0,0787	0,0949	-0,0162	

d. Models 6-45-1

Training with this model produces epochs with 723 iterations. The Table 10 shows the training and Table 11 shown testing schedule.

Table 10. Training Data Model 6-45-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 723		
							Actual	Error	Perf
1	0,1325	0,1430	0,1544	0,1553	0,1272	0,1270	0,1274	-0,0004	
2	0,3915	0,4328	0,4769	0,4811	0,4490	0,4151	0,4151	0,0000	
3	0,1360	0,1447	0,1532	0,1549	0,1669	0,1666	0,1660	0,0006	
4	0,3425	0,3769	0,4036	0,4060	0,3417	0,3412	0,3411	0,0001	
5	0,2978	0,3263	0,3380	0,3401	0,2953	0,2884	0,2885	-0,0001	0,00000034
6	0,4791	0,5255	0,5508	0,5524	0,8649	0,8781	0,8781	0,0000	
7	0,1026	0,1071	0,1163	0,1167	0,1432	0,1424	0,1430	-0,0006	
8	0,1163	0,1213	0,1291	0,1295	0,1204	0,1752	0,1752	0,0000	
9	0,0781	0,0799	0,0829	0,0835	0,0983	0,1026	0,1014	0,0012	
10	0,0800	0,0821	0,0866	0,0866	0,0802	0,0808	0,0818	-0,0010	

Table 11. Test Data Model 6-45-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 723		
							Actual	Error	Perf
1	0,1223	0,1288	0,1405	0,1370	0,1304	0,1223	0,1205	0,0018	
2	0,3840	0,3867	0,4239	0,3911	0,3667	0,3198	0,3631	-0,0433	
3	0,1576	0,1700	0,1829	0,1830	0,1748	0,1670	0,1567	0,0103	
4	0,3158	0,3269	0,3518	0,3273	0,3045	0,2919	0,3171	-0,0252	
5	0,2674	0,2850	0,3102	0,3134	0,2993	0,2691	0,2267	0,0424	0,00194051
6	0,8013	0,8138	0,8728	0,8787	0,8015	0,6926	0,8148	-0,1222	
7	0,1387	0,1473	0,1595	0,1625	0,1526	0,1373	0,1385	-0,0012	
8	0,1655	0,1852	0,1887	0,1998	0,1798	0,1708	0,1650	0,0058	
9	0,0997	0,1050	0,1102	0,1106	0,1069	0,1002	0,1038	-0,0036	
10	0,0800	0,0817	0,0874	0,0868	0,0820	0,0787	0,0793	-0,0006	

e. Models 6-50-1

The training output of this model produces epochs with 317 iterations. The Table 12 shows the training and Table 13 shown testing schedule.

Table 12. Training Data Model 6-50-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch 317		
							Actual	Error	Perf
1	0,1325	0,1430	0,1544	0,1553	0,1272	0,1270	0,1273	-0,0003	0,00000012
2	0,3915	0,4328	0,4769	0,4811	0,4490	0,4151	0,4151	0,0000	
3	0,1360	0,1447	0,1532	0,1549	0,1669	0,1666	0,1662	0,0004	
4	0,3425	0,3769	0,4036	0,4060	0,3417	0,3412	0,3412	0,0000	
5	0,2978	0,3263	0,3380	0,3401	0,2953	0,2884	0,2883	0,0001	
6	0,4791	0,5255	0,5508	0,5524	0,8649	0,8781	0,8781	0,0000	
7	0,1026	0,1071	0,1163	0,1167	0,1432	0,1424	0,1430	-0,0006	
8	0,1163	0,1213	0,1291	0,1295	0,1204	0,1752	0,1751	0,0001	
9	0,0781	0,0799	0,0829	0,0835	0,0983	0,1026	0,1019	0,0007	
10	0,0800	0,0821	0,0866	0,0866	0,0802	0,0808	0,0810	-0,0002	

Table 13. Test Data Model 6-50-1

No	X1	X2	X3	X4	X5	Target (Y1)	Epoch		
							Actual	Error	Perf
1	0,1223	0,1288	0,1405	0,1370	0,1304	0,1223	0,1234	-0,0011	0,00569265
2	0,3840	0,3867	0,4239	0,3911	0,3667	0,3198	0,2567	0,0631	
3	0,1576	0,1700	0,1829	0,1830	0,1748	0,1670	0,1734	-0,0064	
4	0,3158	0,3269	0,3518	0,3273	0,3045	0,2919	0,2580	0,0339	
5	0,2674	0,2850	0,3102	0,3134	0,2993	0,2691	0,2855	-0,0164	
6	0,8013	0,8138	0,8728	0,8787	0,8015	0,6926	0,4657	0,2269	
7	0,1387	0,1473	0,1595	0,1625	0,1526	0,1373	0,1364	0,0009	
8	0,1655	0,1852	0,1887	0,1998	0,1798	0,1708	0,1709	-0,0001	
9	0,0997	0,1050	0,1102	0,1106	0,1069	0,1002	0,0979	0,0023	
10	0,0800	0,0817	0,0874	0,0868	0,0820	0,0787	0,0803	-0,0016	

3 RESULTS AND ANALYSIS

The architectural model was obtained after training and testing data using Matlab and Microsoft Excel for architectural models 5-10-1, 5-15-1, 5-30-1, 5-45-1, and 5-50- 1. 5- Top 15-1 (Table 14) with a Performance/MSE test result of 0.00791984 (Figure 3).

Table 14. Test Results

Algoritma	Arsitektur	Fungsi Training	Epoch (Iterasi)	MSE/Training	MSE Testing/Performance
Fletcher-Reeves	5-10-1	traincgf	40	0,00421454	0,00227787
	5-15-1	traincgf	213	0,00000010	0,00791984
	5-30-1	traincgf	276	0,00034630	0,00055285
	5-45-1	traincgf	723	0,00000034	0,00194051
	5-50-1	traincgf	317	0,00000012	0,00569265

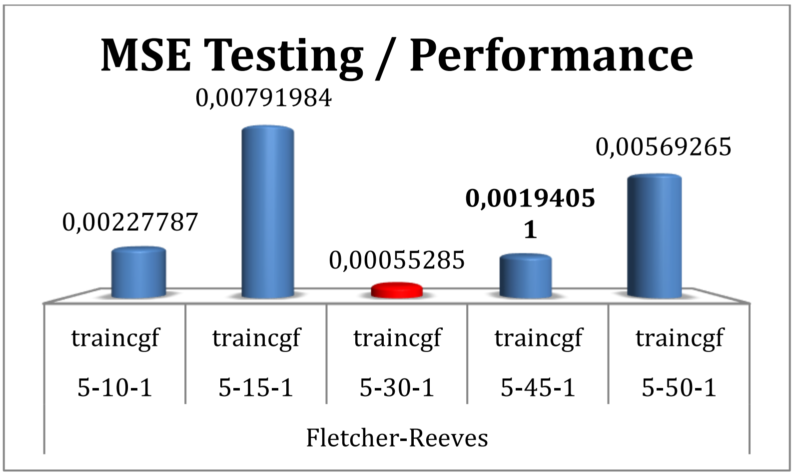

Figure 3. Comparison of Overall Results Model

4 CONCLUSION

Powell-Beale Conjugate Gradient Algorithm with architectural model 6-10-1 can be used to predict Rubber Crop Production in Sumatra because the training time to achieve convergence is not too long and the resulting performance is quite adequate. This algorithm performs better than the other four architectural models, according to the results and discussion. Overall, it is also possible to conclude that the Powell-Beale algorithm (traincgb) is able to achieve a high level of optimization, seen from its ability to generate Performance / MSE test results (low), short convergence time, and relatively fast iteration.

REFERENCES

[1] H. Sulistiani and K. Muludi, "Penerapan Metode Certainty Factor Dalam Mendeteksi Penyakit Tanaman Karet," *Jurnal Pendidikan Teknologi dan Kejuruan*, vol. 15, no. 1, pp. 51–59, 2018, doi: 10.23887/jptk-undiksha.v15i1.13021.

[2] Andrian, Supriadi, and P. Marpaung, "Pengaruh Ketinggian Tempat dan Kemiringan Lereng terhadap Produksi Karet (Hevea brasiliensis Muell. Arg.) di Kebun Hapesong PTPN III Tapanuli Selatan," *E-Journal Agroekoteknologi*, vol. 2, no. 3, pp. 981–989, 2014.

[3] H. Sulistiani, I. Darwanto, and I. Ahmad, "Penerapan Metode Case Based Reasoning dan," *Jurnal Edukasi dan Penelitian Informatika*, vol. 6, no. 1, pp. 23–28, 2020.

[4] I. R. Fauzi, "Alternatif Strategi Pengembangan Industri Barang Jadi Karet Di Indonesia," *Warta Perkaretan*, vol. 32, no. 2, p. 55, 2013, doi: 10.22302/ppk.wp.v32i2.37.

[5] E. Maria and E. Junirianto, "Sistem Pendukung Keputusan Pemilihan Bibit Karet Menggunakan Metode TOPSIS," *Informatika Mulawarman : Jurnal Ilmiah Ilmu Komputer*, vol. 16, no. 1, p. 7, 2021, doi: 10.30872/jim.v16i1.5132.

[6] R. Ardika, A. N. Cahyo, and T. Wijaya, "Dinamika Gugur Daun Dan Produksi Berbagai Klon Karet Kaitannya Dengan Kandungan Air Tanah," *Jurnal Penelitian Karet*, vol. 29, no. 2, pp. 102–109, 2016, doi: 10.22302/ppk.jpk.v29i2.242.

[7] K. Langkat, J. V. No, and S. Utara, "1 , 2 , 3," vol. 6, no. 1, pp. 1–10, 2022.

[8] R. Rosaly and A. Prasetyo, "Pengertian Flowchart Beserta Fungsi dan Simbol-simbol Flowchart yang Paling Umum Digunakan," *Https://Www.Nesabamedia.Com*, vol. 2, p. 2, 2019.

[9] J. Junaidi, "Transformasi Sistem Pemanenan Latex Tanaman Karet: Review," *Jurnal Budidaya Pertanian*, vol. 16, no. 1, pp. 1–10, 2020, doi: 10.30598/jbdp.2020.16.1.1.

[10] I. W. B. W. dan I. G. B. Indrajaya, "Pengaruh jumlah produksi karet, harga , dan investasi terhadap volume ekspor karet indoesia 1996-2010," *Jurnal EP Unud*, vol. 53, no. 9, pp. 1689–1699, 2013.

[11] R. Ramdani, E. P. Purnomo, and R. D. P. Ahsani, "Karet Alam Sebagai Basis Pembangunan Pedesaan dan Peningkatan Tarap Hidup Masyarakat yang Berkelanjutan," *Magelang: Universitas Tidar Magelang*, vol. 44, no. 1, pp. 21–36, 2018.

[12] H. Prastanto, Y. Firdaus, S. Puspitasari, A. Ramadhan, and A. F. Falaah, "Sifat Fisika Aspal Modifikasi Karet Alam Pada Berbagai Jenis Dan Dosis Lateks Karet Alam," *Jurnal Penelitian Karet*, no. October, pp. 65–76, 2018, doi: 10.22302/ppk.jpk.v36i1.444.

[13] D. Syahputra, "Analisis Faktor - Faktor Yang Mempengaruhi Pendapatan Petani Karet Di Kecamatan Seunagan Timur Kabupaten Nagan Raya," *Jurnal Ilmiah Mahasiswa Agroinfo Galuh*, vol. 2, no. 4, pp. 85–93, 2018.

[14] G. Claudia, E. Yulianto, and M. K. Mawardi, "Pengaruh Produksi Karet Nilai Tukar Terhadap Volume Ekspor Ka ...," *Jurnal Administrasi Bisnis (JAB)*, vol. 35, no. 1, pp. 165–171, 2016.

[15] S. Anam, T. Adriyanto, and W. M. K, "Diagnosis Diabetes Mellitus Menggunakan Algoritma Jaringan Syaraf Tiruan Backpropagation dengan Metode Conjugate Gradient Fletcher-Reeves Adaptive Gain," pp. 47–52, 2017, doi: 10.21063/pimimd4.2017.47-52.

[16] L. F. Syarifa, D. S. Agustina, C. Nancy, and M. Supriadi, "Dampak Rendahnya Harga Karet Terhadap Kondisi Sosial Ekonomi Petani Karet Di Sumatera Selatan," *Jurnal Penelitian Karet*, vol. 34, no. 1, p. 119, 2016, doi: 10.22302/jpk.v0i0.218.

[17] S. Damanik, "Pengembangan Karet (Havea brasiliensis) Berkelanjutan di Indonesia," *Perspektif*, vol. 11, no. 1, pp. 91–102, 2012.

[18] A. Wanto, A. P. Windarto, D. Hartama, and I. Parlina, "Use of Binary Sigmoid Function And Linear Identity In Artificial Neural Networks For Forecasting Population Density," *IJISTECH (International Journal Of Information System & Technology)*, vol. 1, no.

1, p. 43, 2017, doi: 10.30645/ijistech.v1i1.6.

[19] R. M. Firzatullah, “Sistem Pendukung Keputusan Penentuan Uang Kuliah Tunggal Universitas XYZ Menggunakan Algoritma Backpropagation,” *PETIR*, vol. 14, no. 2, pp. 170–180, Sep. 2021, doi: 10.33322/petir.v14i2.996.

[20] A. Desiani, “Kajian Pengenalan Wajah Dengan Menggunakan Metode Face-Arg Dan Jaringan Syaraf Tiruan,” vol. 5, no. 2, pp. 99–111, 2007.

[21] A. F. H. MUNZIR, , ADIWIJAYA, and A. ADITSANIA, “Analisis Reduksi Dimensi Pada Klasifikasi Microarray Menggunakan Mbp Powell Beale,” *E-Jurnal Matematika*, vol. 7, no. 1, p. 17, 2018, doi: 10.24843/mtk.2018.v07.i01.p179.

[22] A. Wanto, “Optimasi Prediksi Dengan Algoritma Backpropagation Dan Conjugate Gradient Beale-Powell Restarts,” *Jurnal Nasional Teknologi & Sistem Informasi*, vol. 3, no. 3, pp. 370–380, 2018.

[23] S. Gessawati, F. Ilmu, S. Dan, and I. Politik, “14.104.120.75,” 2017.

[24] J. F. Simanjuntak, R. Winanjaya, and W. Robiansyah, “Peramalan Hasil Produksi Karet di Sumatra Utara dengan Algoritma Backpropagation Forecasting of Rubber Production in North Sumatra with Backpropagation Algorithm,” vol. 1, no. 3, 2022, doi: 10.55123/jomlai.v1i3.917.