



Implementation of Artificial Intelligence in Predicting the Value of Indonesian Oil and Gas Exports With BP Algorithm

Agus Perdana Windarto¹, Linda Sari Dewi², Dedy Hartama³

¹*Department of Information Systems and Informatics Engineering, STIKOM Tunas Bangsa Pematangsiantar*

³*Department of Information Systems and Informatics Engineering, STIKOM Tunas Bangsa Pematangsiantar*

²*Department of Information Systems, STMIK Nusa Mandiri Jakarta*

Abstract— Export is an activity of selling goods to another country. Indonesia's main export capital is natural wealth. From natural wealth owned, can be produced various kinds of export goods. Goods that can be exported are goods that are in demand and needed by overseas buyers. Indonesian export commodities consist of petroleum and gas (oil and gas) as well as non-oil and gas. This study aims to predict the value of Indonesia's oil and gas exports with the Network of Artificial Backpropagation. Data obtained from customs documents of the Directorate General of Customs and Excise (PEB and PIB) obtained from the Central Bureau of Statistics with url <https://www.bps.go.id/>. The data used are the last 40 years (1975-2014) data which is divided into 4 decades (10 years/decade). From five architectural models 10-2-1, architecture 10-5-1, architecture 10-2-5-1, architecture 10-5-2-1 and architecture 10-10-1 obtained the best 10-5-1 model With epoch 28630, MSE training 0,0010005738, MSE testing 0,0034417506. With this architecture model obtained 90% prediction accuracy for the export value of Indonesia.

Keywords— Oil and Gas Exports, Backpropagation, Indonesia, Prediction

I. INTRODUCTION

Exports are activities of selling goods to other countries. Indonesia's main export capital is natural wealth. From natural wealth owned, can be produced various kinds of export goods. Goods that can be exported are goods that are in demand and needed by overseas buyers. Indonesian export commodities consist of petroleum and gas (oil and gas) as well as non-oil and gas. Indonesia is one of oil and gas exporter to destination country. Some of the countries that are export destinations of Indonesia include the United States, Germany, Japan, China, Taiwan, and Australia. The country that the main export destination of Indonesia is the United States. This study aims to analyze the value of Indonesia's oil and gas exports by using computer science. One of the analysis process that can be done is forecasting the value of oil and gas exports in indonesia.

Artificial Neural Network (ANN) is able to make introductions of past-based activities or learn from experience. Past data will be studied by Artificial Neural Networks so that it has the ability to make decisions on data that has not been studied. Artificial Neural Network is one branch of Artificial Inteligent. Artificial Neural Networks are the processing paradigm of information that is inspired by the Biological Neural cell system, just as the brain processes information. Backpropagation is one of the artificial neural network algorithms that is often used to solve complex problems related to input identification, prediction, pattern recognition, and so on. Repeated training will result in a network that responds correctly to its input. It is an advantage of Backpropogations that can bring about a system that is resistant to damage and works consistently well.

II. METHODS AND MATERIAL

2.1. Artificial Intelligence

AI is a field of study based on the premise that intelligent thought can be regarded as a form of computation - one that can be formalized and ultimately mechanized. To achieve this, however, two major issues need to be addressed. The first issue is knowledge representation, and the second is knowledge manipulation [1]. The main aim of Artificial Intelligence (AI) is to study how to build artificial systems that perform tasks normally performed by human beings. This concept was introduced in 1956 in the Dartmouth conference. From that moment on a lot of effort has been made and many goals have been achieved but unfortunately many failures as well. Today, the AI is a very important discipline and it includes a number of well-recognized and mature areas including Expert Systems [2-4], Fuzzy Logic [5-8], Genetic Algorithms [9-11], Language Processing, Logic Programming, Planning and Scheduling, Neural Networks and Robotics [12]. The general problem of simulating intelligence has been simplified to specific sub-problems which have certain characteristics or capabilities that an intelligent system should exhibit. The following characteristics have received the most attention:

1. Deduction, reasoning, problem solving (embodied agents, neural networks, statistical approaches to AI);
2. Knowledge representation (ontologies);
3. Planning (multi-agent planning and cooperation);
4. Learning (machine learning);
5. Natural Language Processing (information retrieval – text mining, machine translation);
6. Motion and Manipulation (navigation, localization, mapping, motion planning);
7. Perception (speech recognition, facial, recognition, object recognition);
8. Social Intelligence (empathy simulation);
9. Creativity (artificial intuition, artificial imagination); and
10. General Intelligence (Strong AI).

2.2. Artificial Neural Networks (NN)

Artificial Neural Network (ANN) is a computational model, which is based on Biological Neural Network. Artificial Neural Network is often called as Neural Network (NN) (See Figure 1). From Figure 1, to build artificial neural network, artificial neurons, also called as nodes, are interconnected [13,14]. The architecture of NN is very important for performing a particular computation. Some neurons are arranged to take inputs from outside environment. These neurons are not connected with each other, so the arrangement of these neurons is in a layer, called as Input layer. All the neurons of input layer are producing some output, which is the input to next layer. The architecture of NN can be of single layer or multilayer. In a single layer Neural Network, only one input layer and one output layer is there, while in multilayer neural network, there can be one or more hidden layer. An artificial neuron is an abstraction of biological neurons and the basic unit in an ANN [15,16]. The Artificial Neuron receives one or more inputs and sums them to produce an output. Usually the sums of each node are weighted, and the sum is passed through a function known as an activation or transfer function. The objective here is to develop a data classification algorithm that will be used as a general-purpose classifier. To classify any database first, it is required to train the model. The proposed training algorithm used here is a Hybrid BP-GA [17,18]. After successful training, user can give unlabeled data to be classified.

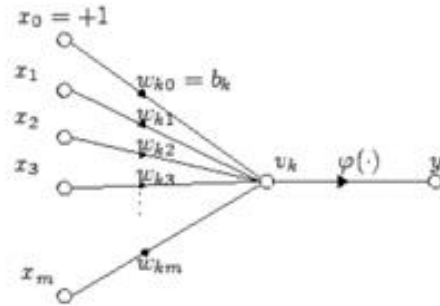


Figure 1. ANN Model

2.3. Architecture of Backpropagation

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 descent 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 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 [19].

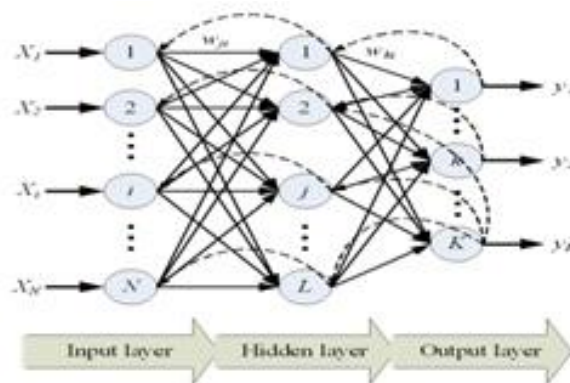


Figure 2. Back-propagation ANN

Each of these layers must be either of the following:

1. Input Layer – This layer holds the input for the network
2. Output Layer – This layer holds the output data, usually an identifier for the input.
3. Hidden Layer – This layer comes between the input layer and the output layer. They serve as a propagation point for sending data from the previous layer to the next layer [20].

2.4. Backpropagation Neural Network

Phases in Backpropagation Technique algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation involves the following steps:

1. Forward propagation of a training pattern's input is given through the neural network in order to generate the propagation's output activations.
2. Back propagation of the output activations propagation through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight Update
For each weight-synapse:
1. Multiply its input activation and output delta to get the gradient of the weight.
2. Bring the weight in the direction of the gradient by adding a ratio of it from the weight.

This ratio impacts on the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight designates where the error is increasing; this is why the weight must be updated in the opposite direction. The phases 1 and 2 are repeated until the performance of the network is satisfactory [21,22].

III. RESULTS AND DISCUSSION

3.1. Defining Input and Target

Data on the value of Indonesian oil and gas exports will then be processed using Artificial Neural Network with backpropagation method. In order for data to be recognized by Artificial Neural Networks, the data must be represented in numerical form between 0 and 1, both variables and contents which are input data of oil and gas export value of Indonesia as the introduction of pattern and output which is the prediction of Indonesian oil and gas export value obtained from The best architectural model when determining the best pattern. This is because the network uses a bin sigmoid activation function (logsig) that ranges from 0 to 1. The values used are obtained based on the categories of each variable as well as to make it easier to remember in defining it.

3.2. Input Determination

Value Input Determination of Indonesian oil and gas exports is a reference in making a decision on the assessment by using Artificial Neural Network. The input determination is determined by looking at the data dependency. In this case the data used is the data of oil and gas export value Indonesia within 40 years from 1975-2015. The data comes from the Central Bureau of Statistics with the website url: <https://www.bps.go.id>. Determination of input is the value of oil and gas exports each year which is divided into 4 decades (10 years / decade).

This data will later be transformed to a data between 0 to 1 before the training and testing using Artificial Neural Network backpropagation method with the formula:

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

3.3. Targeting

The target data is the total value of oil and gas exports Indonesia in 4 decades (10 years / decade) where decade-1 becomes input and decade-2 becomes target, decade-2 becomes input and decade-3 becomes target, decade-3 becomes input and decade -4 becomes the target. This is done so that all criteria get the same opportunity to be targeted. In other words, target setting by using the rotation pattern.

3.4. Data Processing

Data processing is done with the help of Matlab 6.1 software application. Sample Data is the value of Indonesian oil and gas exports. This data will be used in training data and test data. Samples of data that have been processed and transformed can be seen in the following table

Table 1. Sample Data - Value (Million US \$)

First Decade	Year	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
	Value	7102,50	8546,50	7297,80	7438,50	8870,90	17781,60	20663,20	18399,30	16140,70	16018,10
Second Decade	Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
	Value	12717,80	8276,60	8556,00	7681,60	8678,80	11071,10	10894,90	10670,90	9745,80	9693,60
Third Decade	Year	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
	Value	10464,40	11721,80	11622,50	7872,10	9792,20	14366,60	12636,30	12112,70	13651,40	15645,30
Fourth Decade	Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	Value	19231,60	21209,50	22088,60	29126,30	19018,30	28039,60	41477,00	36977,30	32633,03	30018,80

Table 2. Data Transformation

First Decade	Year	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984
	Value	0,10000	0,13361	0,10455	0,10782	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749
Second Decade	Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
	Value	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030
Third Decade	Year	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
	Value	0,17824	0,20751	0,20519	0,11791	0,16260	0,26906	0,22879	0,21660	0,25241	0,29882
Fourth Decade	Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	Value	0,38228	0,42831	0,44877	0,61256	0,37732	0,58727	0,90000	0,79528	0,69417	0,63333

source : <https://www.bps.go.id>

Table 3. Training data, Test data and forecasting data

No	Name	Input										Target
		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	
1	Pattern 1	0,10000	0,13361	0,10455	0,10782	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069
2	Pattern 2	0,13361	0,10455	0,10782	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732
3	Pattern 3	0,10455	0,10782	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383
4	Pattern 4	0,10782	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348
5	Pattern 5	0,14116	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669
6	Pattern 6	0,34854	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236
7	Pattern 7	0,41560	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826
8	Pattern 8	0,36291	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305
9	Pattern 9	0,31035	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152
10	Pattern 10	0,30749	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030
11	Pattern 11	0,23069	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824
12	Pattern 12	0,12732	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824	0,20751
13	Pattern 13	0,13383	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824	0,20751	0,20519
14	Pattern 14	0,11348	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824	0,20751	0,20519	0,11791
15	Pattern 15	0,13669	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824	0,20751	0,20519	0,11791	0,16260
16	Pattern 16	0,19236	0,18826	0,18305	0,16152	0,16030	0,17824	0,20751	0,20519	0,11791	0,16260	0,26906

No	Name	Input										Target
	16	236	26	05	52	30	24	51	19	91	60	
17	Pattern 17	0,18 826	0,183 05	0,161 52	0,160 30	0,178 24	0,207 51	0,205 19	0,117 91	0,162 60	0,269 06	0,22879
18	Pattern 18	0,18 305	0,161 52	0,160 30	0,178 24	0,207 51	0,205 19	0,117 91	0,162 60	0,269 06	0,228 79	0,21660
19	Pattern 19	0,16 152	0,160 30	0,178 24	0,207 51	0,205 19	0,117 91	0,162 60	0,269 06	0,228 79	0,216 60	0,25241
20	Pattern 20	0,16 030	0,178 24	0,207 51	0,205 19	0,117 91	0,162 60	0,269 06	0,228 79	0,216 60	0,252 41	0,29882
21	Pattern 21	0,17 824	0,207 51	0,205 19	0,117 91	0,162 60	0,269 06	0,228 79	0,216 60	0,252 41	0,298 82	0,38228
22	Pattern 22	0,20 751	0,205 19	0,117 91	0,162 60	0,269 06	0,228 79	0,216 60	0,252 41	0,298 82	0,382 28	0,42831
23	Pattern 23	0,20 519	0,117 91	0,162 60	0,269 06	0,228 79	0,216 60	0,252 41	0,298 82	0,382 28	0,428 31	0,44877
24	Pattern 24	0,11 791	0,162 60	0,269 06	0,228 79	0,216 60	0,252 41	0,298 82	0,382 28	0,428 31	0,448 77	0,61256
25	Pattern 25	0,16 260	0,269 06	0,228 79	0,216 60	0,252 41	0,298 82	0,382 28	0,428 31	0,448 77	0,612 56	0,37732
26	Pattern 26	0,26 906	0,228 79	0,216 60	0,252 41	0,298 82	0,382 28	0,428 31	0,448 77	0,612 56	0,377 32	0,58727
27	Pattern 27	0,22 879	0,216 60	0,252 41	0,298 82	0,382 28	0,428 31	0,448 77	0,612 56	0,377 32	0,587 27	0,90000
28	Pattern 28	0,21 660	0,252 41	0,298 82	0,382 28	0,428 31	0,448 77	0,612 56	0,377 32	0,587 27	0,900 00	0,79528
29	Pattern 29	0,25 241	0,298 82	0,382 28	0,428 31	0,448 77	0,612 56	0,377 32	0,587 27	0,900 00	0,795 28	0,69417
30	Pattern 30	0,29 882	0,382 28	0,428 31	0,448 77	0,612 56	0,377 32	0,587 27	0,900 00	0,795 28	0,694 17	0,63333

3.5. Defining Output

The expected result at this stage is the best pattern architecture to predict the value of Indonesian oil and gas exports. Test results are as follows::

1. To know the prediction of oil and gas export value Indonesia based on oil and gas export value. The output of this prediction is the best architectural pattern by looking at the minimum error.
2. Categorization Output training and testing

The category for output is determined by the minimum error rate of the target. Restrictions on these categories are listed in the following table:

Table 4. Categorization Data

No	Description	Minimum Error
1	True	0.01 - 0.001
2	False	>0.01

The architectural models used for pattern recognition are 10-2-1, 10-5-1, 10-2-5-1, 10-5-2-1 and 10-10-1. The selection of the best architectural pattern on Artificial Neural Network Backpropagation becomes a reference to predict the value of Indonesian oil and gas exports. As in table 3, patterns 1 to 10 patterns are used for training data, patterns 11 to 20 patterns are used for test data. Training and testing data is the stage of obtaining the best architectural pattern. Pattern 21 to 30 is the forecasting data used after obtaining the best architecture on Artificial Neural Network Backpropagation.

A. Training dan Testing Architecture 10-2-1

The results of the training (patterns 1 to 10) and testing (pattern 11 to 20). After the iteration, the minimum error is found on epoch 113939. For more details see the drawings and the results of the training and test in the table as follows :

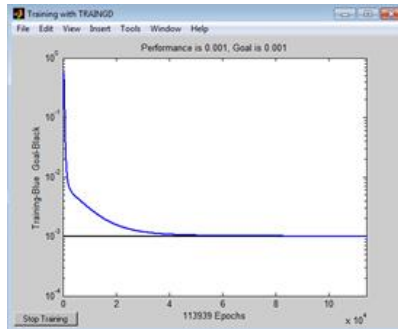


Figure 3. Goal Training Model 10-2-1

Table 5. Training Results and Testing Model 10-2-1

Train						Test					
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
1	Pattern 1	0,23069	0,196	0,03449	0,0011895601	1	Pattern 11	0,17824	0,171	0,00764	0,0000583696
2	Pattern 2	0,12732	0,173	-0,04568	0,0020866624	2	Pattern 12	0,20751	0,172	0,03601	0,0012967201
3	Pattern 3	0,13383	0,159	-0,02557	0,0006538249	3	Pattern 13	0,20519	0,172	0,03369	0,0011350161
4	Pattern 4	0,11348	0,157	-0,04342	0,0018852964	4	Pattern 14	0,11791	0,172	-0,05399	0,0029149201
5	Pattern 5	0,13669	0,148	-0,01121	0,0001256641	5	Pattern 15	0,16260	0,17	-0,00740	0,0000547600
6	Pattern 6	0,19236	0,148	0,04456	0,0019855936	6	Pattern 16	0,26906	0,171	0,09856	0,0097140736
7	Pattern 7	0,18826	0,151	0,03716	0,0013808656	7	Pattern 17	0,22879	0,172	0,05669	0,0032137561
8	Pattern 8	0,18305	0,159	0,02445	0,0005978025	8	Pattern 18	0,21660	0,171	0,04560	0,0020793600
9	Pattern 9	0,16152	0,167	-0,00538	0,0000289444	9	Pattern 19	0,25241	0,171	0,08141	0,0066275881
10	Pattern 10	0,16030	0,169	-0,00830	0,0000688900	10	Pattern 20	0,29882	0,173	0,12582	0,0158306724
				Total	0,0100031040					Total	0,0429252361
				MSE	0,00100031					MSE	0,004292524
										Accuracy	90

B. Training dan Testing Architecture 10-5-1

The results of the training (patterns 1 to 10) and testing (pattern 11 to 20). After the iteration, there is a minimum error in epoch 28630. For more details see the drawings and the results of the training and test in the table as follows :

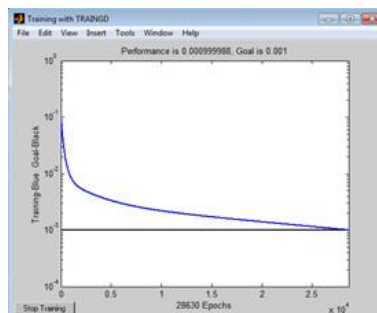


Figure 4. Goal Training Model 10-5-1

Table 6. Training Results and Testing Model 10-5-1

Train						Test					
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
1	Pattern 1	0,23069	0,2462	-0,01551	0,0002405601	1	Pattern 11	0,17824	0,2127	-0,03446	0,0011874916
2	Pattern 2	0,12732	0,0894	0,03792	0,0014379264	2	Pattern 12	0,20751	0,2364	-0,02889	0,0008346321
3	Pattern 3	0,13383	0,0742	0,05963	0,0035557369	3	Pattern 13	0,20519	0,2236	-0,01841	0,0003389281

Train						Test					
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
4	Pattern 4	0,11348	0,0952	0,01828	0,0003341584	4	Pattern 14	0,11791	0,2199	-0,10199	0,0104019601
5	Pattern 5	0,13669	0,1796	-0,04291	0,0018412681	5	Pattern 15	0,16260	0,2382	-0,07560	0,0057153600
6	Pattern 6	0,19236	0,1915	0,00086	0,0000007396	6	Pattern 16	0,26906	0,3185	-0,04944	0,0024443136
7	Pattern 7	0,18826	0,174	0,01426	0,0002033476	7	Pattern 17	0,22879	0,2735	-0,04471	0,0019989841
8	Pattern 8	0,18305	0,1442	0,03885	0,0015093225	8	Pattern 18	0,21660	0,1159	0,10070	0,0101404900
9	Pattern 9	0,16152	0,1658	-0,00428	0,0000183184	9	Pattern 19	0,25241	0,2158	0,03661	0,0013402921
10	Pattern 10	0,16030	0,1897	-0,02940	0,0008643600	10	Pattern 20	0,29882	0,3027	-0,00388	0,0000150544
				Total	0,0100057380					Total	0,0344175061
				MSE	0,001000574					MSE	0,003441751
										Accuracy	80

C. Training dan Testing Architecture 10-2-5-1

The results of the training (patterns 1 to 10) and testing (pattern 11 to 20). After the iteration, the minimum error is found on epoch 85404. For more details see the drawings and the results of the training and test in the table as follows:

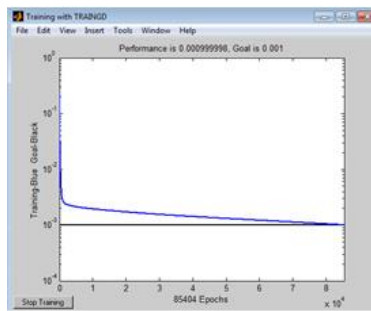


Figure 5. Goal Training Model 10-2-5-1

Table 7. Training Results and Testing Model 10-2-5-1

Train						Test					
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
1	Pattern 1	0,23069	0,1817	0,04899	0,0024000201	1	Pattern 11	0,17824	0,1535	0,02474	0,0006120676
2	Pattern 2	0,12732	0,1749	-0,04758	0,0022638564	2	Pattern 12	0,20751	0,1544	0,05311	0,0028206721
3	Pattern 3	0,13383	0,1561	-0,02227	0,0004959529	3	Pattern 13	0,20519	0,1545	0,05069	0,0025694761
4	Pattern 4	0,11348	0,1553	-0,04182	0,0017489124	4	Pattern 14	0,11791	0,1581	-0,04019	0,0016152361
5	Pattern 5	0,13669	0,1673	-0,03061	0,0009369721	5	Pattern 15	0,16260	0,1531	0,00950	0,0000902500
6	Pattern 6	0,19236	0,167	0,02536	0,0006431296	6	Pattern 16	0,26906	0,1524	0,11666	0,0136095556
7	Pattern 7	0,18826	0,162	0,02626	0,0006895876	7	Pattern 17	0,22879	0,166	0,06279	0,0039425841
8	Pattern 8	0,18305	0,1565	0,02655	0,0007049025	8	Pattern 18	0,21660	1,1708	-0,95420	0,9104976400
9	Pattern 9	0,16152	0,154	0,00752	0,0000565504	9	Pattern 19	0,25241	0,1547	0,09771	0,0095472441
10	Pattern 10	0,16030	0,1528	0,00750	0,0000562500	10	Pattern 20	0,29882	0,1735	0,12532	0,0157051024
				Total	0,0099961340					Total	0,9610098281
				MSE	0,000999613					MSE	0,096100983
										Accuracy	70

D. Training dan Testing Architecture 10-5-2-1

The results of the training (patterns 1 to 10) and testing (pattern 11 to 20). After the iteration, the minimum error is found on epoch 472135. For more details see the drawings and the results of the training and test in the table as follows:

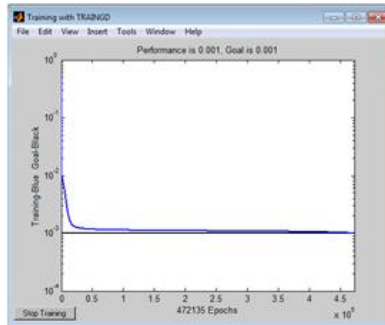


Figure 6. Goal Training Model 10-5-2-1

Table 8. Training Results and Testing Model 10-5-2-1

Train						Test					
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
1	Pattern 1	0,23069	0,158	0,07269	0,0052838361	1	Pattern 11	0,17824	0,1592	0,01904	0,0003625216
2	Pattern 2	0,12732	0,1591	0,03178	0,0010099684	2	Pattern 12	0,20751	0,1548	0,05271	0,0027783441
3	Pattern 3	0,13383	0,1557	0,02187	0,0004782969	3	Pattern 13	0,20519	0,1581	0,04709	0,0022174681
4	Pattern 4	0,11348	0,1501	0,03662	0,0013410244	4	Pattern 14	0,11791	0,1582	-0,04029	0,0016232841
5	Pattern 5	0,13669	0,1546	0,01791	0,0003207681	5	Pattern 15	0,16260	0,1592	0,00340	0,0000115600
6	Pattern 6	0,19236	0,1609	0,03146	0,0009897316	6	Pattern 16	0,26906	0,1589	0,11016	0,0121352256
7	Pattern 7	0,18826	0,1687	0,01956	0,0003825936	7	Pattern 17	0,22879	0,1586	0,07019	0,0049266361
8	Pattern 8	0,18305	0,1849	0,00185	0,0000034225	8	Pattern 18	0,21660	0,1593	0,05730	0,0032832900
9	Pattern 9	0,16152	0,1738	0,01228	0,0001507984	9	Pattern 19	0,25241	0,158	0,09441	0,0089132481
10	Pattern 10	0,16030	0,1661	0,00580	0,0000336400	10	Pattern 20	0,29882	0,1588	0,14002	0,0196056004
				Total	0,0099940800					Total	0,0558571781
				MSE	0,000999408					MSE	0,005585718
										Accuracy	80

E. Training dan Testing Architecture 10-10-1

The results of the training (patterns 1 to 10) and testing (pattern 11 to 20). After the iteration, the minimum error is found on epoch 37794. For more details see the drawings and the results of the training and test in the table as follows:

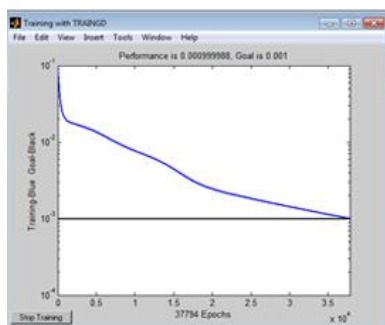


Figure 7. Goal Training Model 10-10-1

Table 9. Training Results and Testing Model 10-10-1

Train					Test						
No	Pattern	Target	Output	Error	SSE	No	Pattern	Target	Output	Error	SSE
1	Pattern 1	0,23069	0,2443	0,01361	0,0001852321	1	Pattern 11	0,17824	0,1885	-0,01026	0,0001052676
2	Pattern 2	0,12732	0,0717	0,05562	0,0030935844	2	Pattern 12	0,20751	0,1892	0,01831	0,0003352561
3	Pattern 3	0,13383	0,07	0,06383	0,0040742689	3	Pattern 13	0,20519	0,171	0,03419	0,0011689561
4	Pattern 4	0,11348	0,111	0,00248	0,0000061504	4	Pattern 14	0,11791	0,1562	-0,03829	0,0014661241
5	Pattern 5	0,13669	0,1408	0,00411	0,0000168921	5	Pattern 15	0,16260	0,1418	0,02080	0,0004326400
6	Pattern 6	0,19236	0,1971	0,00474	0,0000224676	6	Pattern 16	0,26906	0,2141	0,05496	0,0030206016
7	Pattern 7	0,18826	0,1726	0,01566	0,0002452356	7	Pattern 17	0,22879	0,2199	0,00889	0,0000790321
8	Pattern 8	0,18305	0,1718	0,01125	0,0001265625	8	Pattern 18	0,21660	0,0986	0,11800	0,0139240000
9	Pattern 9	0,16152	0,2085	0,04698	0,0022071204	9	Pattern 19	0,25241	0,1299	0,12251	0,0150087001
10	Pattern 10	0,16030	0,1657	0,00540	0,0000291600	10	Pattern 20	0,29882	0,1299	0,16892	0,0285339664
				Total	0,0100066740					Total	0,0640745441
				MSE	0,001000667					MSE	0,006407454
										Accuracy	70

F. The Best Architecture Model

The result of Matlab 6.1 application software used for architectural model 10-2-1, architecture 10-5-1, architecture 10-2-5-1, architecture 10-5-2-1 and architecture 10-10-1 is obtained pattern The best architecture. From this pattern will be used to predict the value of Indonesian oil and gas exports. Assessment of the best architectural models is seen from several aspects such as epoch, minimum error, MSE training, MSE testing, timing and accuracy of the truth. For more details can be seen in the following:

Table 10. Recapitulation of Architectural Model

Criteria	Pattern			
	10-2-1	10-5-1	10-2-5-1	10-5-2-1
Epoch	113939	28630	85404	472135
Mse Training	0,0010003104	0,0010005738	0,0009996134	0,0009994080
Mse Testing	0,0042925236	0,0034417506	0,0961009828	0,0055857178
Accury Of Truth	90%	80%	70%	80%

Table 10 it can be seen that the best architectural model used to make predictions from a series of model trials is 10-5-1. This reason is taken from several criteria. Basically architecture 10-2-1 has a higher accuracy than architecture 10-5-1. While architecture 10-5-1 and architecture 10-5-2-1 have the same level of accuracy. The architecture 10-5-1 as the best pattern as seen from several aspects such as epoch, MSE training and MSE testing with 80% accuracy.

G. Predicted Value of Indonesian Oil and Gas Exports

The results of the design that made the best training is produced that have the results of accuracy or goodness and good learning. To predict the value of Indonesian oil and gas exports, the data we use are predictive data (pattern 21 to 30) by determining x.max (for the original maximum data) and x.min (for the original minimum data) from Backpropogation. The architectural model and the formula used to predict the value of Indonesian oil and gas exports is architectural model 10-5-1 and

$$x = \frac{(x' - 0.1)(x_{max} - x_{min})}{0.8} + x_{min}$$

For more details please look at the following table.

No	Name	Actual value (Million US\$)	Y Actual	Y Prediction	e	value Prediction (Million US\$)
1	Pattern 21	19231,6	0,38228	0,38118	0,00110	19184,27739
2	Pattern 22	21209,5	0,42831	0,42701	0,00130	21153,50656
3	Pattern 23	22088,6	0,44877	0,44727	0,00150	22024,04077
4	Pattern 24	29126,3	0,61256	0,61086	0,00170	29053,19634
5	Pattern 25	19018,3	0,37732	0,37542	0,00190	18936,78099
6	Pattern 26	28039,6	0,58727	0,58517	0,00210	27949,34521
7	Pattern 27	41477	0,90000	0,89770	0,00230	41378,17331
8	Pattern 28	36977,3	0,79528	0,79278	0,00250	36869,95764
9	Pattern 29	32633,03	0,69417	0,39417	0,30000	19742,43333
10	Pattern 30	30018,8	0,63333	0,63043	0,00290	29894,08254
					90%	

IV. CONCLUSION

The exposure of articles that have been done, obtained the conclusion

- Artificial Neural Network Method has adaptive nature of the network trying to achieve stability again to achieve the expected output. This is due to the learning process with the adjustment of connection weights
- Determination of optimum network parameters can only be done based on the learning process and the determination of the magnitude of errors so that the length of study time can not be determined with certainty.
- The number of iterations can not be determined by the magnitude of the desired pattern recognition accuracy but determined by the network parameters used, the initial conditions of the network and the characteristics of the input data.
- The speed to obtain the pattern of training results is not determined by the computational speed but is determined by the network parameters and solution space sought.
- The smaller the level of accuracy error used will be the smaller deviations of the results of ANN with the desired target.
- With architectural model 10-5-1, can predict the value of Indonesia's oil and gas exports by showing performance above 80%

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