Comparison of Extreme Learning Machine and Neural Network Methods on Automatic Pressure Application of Plant Air Receiver Based on Microcontroller

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Abstract*—One Chemical Company is a state-owned factory engaged in the production of fertilizers. Especially in factory which is a supporter of air needs for line to line needs in Plant Air Receiver. The air requirement is supplied by three air compressors using an electric power. Air is accommodated on a large tube that is called D923 Plant Air Receiver tube. After meet the required air pressure, air will be channeled to the Plant Air Receiver line. However, three compressors still use manual systems where the operator goes down to the plant to turn off and turn on the compressor and the compressor is still running independently. If the compressor burns continuously in hot conditions then the compressor lifetime will shorten. With the above problems, the researcher tries to create a system of air pressure plant automation receiver by using microcontroller, as a main control of the system are using ELM and NN. Both of them are used for controlling the air valve filling and air pressure measurement process using MPX5500DP sensor and compressor temperature measurement using DS18B20 to make two compressors as main compressor and backup compressor. It is expected to be used to assist in the process of control and monitoring of air filling so it can be controlled through control room.

Keywords*—plant air receiver, microcontroller, MPX5500DP sensor, DS18B20, ELM, NN.

I. INTRODUCTION

Chemical Company is a state-owned factory engaged in the production of fertilizers. The fertilizer production process requires air power to support all production needs or based on numerical analysis [1-3]and artificial intelligent [4-15]. Particularly in the Plant Air Receiver in chemical plant 1 which has 6 air needs lines, namely bins big blaster, pug mill (09-M-108), to sulfuric and line (40-SA-C3-b-102), to 25-NHL -LI-101-C25 and to small users process area. The air supply is supplied by 3 compressors with electric power. Compressor is a machine or mechanical device that serves to increase pressure or compress the gas or air fluid. Compressors are usually use electric motors. The 3 compressors are still running independently so if one compressor cannot meet the set point on the tube then the plant air receiver must turn on the other compressor manually and the compressor will ignite continuously with hot conditions that will shorten the compressor lifetime because the compressor also requires backup for cooling time before working back. The damaged compressor will lead to the waste of the time and cost because it must bring maintenance and this problem will make the production process becomes disrupted and even stalled. Therefore, in this research has made a temperature automation equipment and plant air receiver pressure.

Measurements of air pressure on the receiver's air tube using the MPX5500DP sensor and the compressor temperature will be detected by DS18B20 sensor and the motor as valve control on the air receiver tube faucet as well as the ELM and NN methods used to opening the control valve. Microcontroller is used as the main control in air filling process and visual application program is using visual basic application that serves as HMI to monitor the process and set the value of air pressure for line-line on plant air receiver.

In this paper will compare two methods, first is *Extreme Learning Machine* (ELM) and second is *Neural Network* (NN). ELM is a learning algorithm for single-hidden layer feed forward Neural Networks (SFNNs) [16] and internal parameters tailored to the ELM iteration unlike the Neural Network method, but randomly or calculated analytically [17]. Neural Network (NN) is one of the artificial intelligence methods, it is able to identify pattern, signal processing, and system forecasting by learning the statistical data [18]. The challenge in this paper is to apply the ELM and NN methods. The predicted results of both methods must have a high degree of accuracy. So, we can compare and know the advantages and disadvantages of both methods.

II. METHODOLOGY

The purpose of this research is to explain about the application of Extreme Learning Machine and Back Propagation Neural Network. Both methods are applied to the tool to get the optimum results. The input of the system is the air pressure on the compressor1, compressor2 and the air container detected by the MPX5500DP sensor, and the output on the system is 2 valve rotation (0-90^0) driven by the servo motor.

A. Selecting a Designing System

This tool works automatically using Extreme Learning Machine and Back Propagation Neural Network to control the open air valve cap and air pressure measurement process using MPX5500DP sensor and compressor temperature measurement using DS18B20 sensor to make two compressors working as main compressor and backup compressor.

The system work steps are as follows:

1. Enable the system
2. Include set point tube of plant air receiver as needed
3. The DS18B20 sensor will detect the temperature of all three sensors
4. The system will select 2 compressors that will work as main compressor and backup compressor according to the temperature of the compressor.
5. Selection of compressors 1 and 2 based on temperature:
   a. When the temperature of the compressor A Low, compressor B Low, and Compressor C Low then Compressor A and Compressor B are ON.
   b. When compressor temperature A is low, compressor B is low, and compressor C is high then compressor A and compressor B are ON.
   c. When the temperature of the compressor A is low, the compressor B is high, and the compressor C is low then the Compressor A and Compressor C are ON.
   d. When the temperature of compressor A is high, compressor B is low, and compressor C is low then compressor B and compressor C are ON
6. The ELM and NN process of opening the valve control from 0-100% between (0-90^0) based on 3 inputs; 2 compressor pressures from the MPX5500DP sensor and 1 set point input, to determine when the compressor is working alone or working concurrently to reach the set point.

B. Designing Hardware

Hardware is designed with a monitoring process that can run in a real time. The placement of the hardware (sensors, controllers, and actuators) is designed in such a way to provide a stable layout and buffer. Here is a hardware system block diagram.

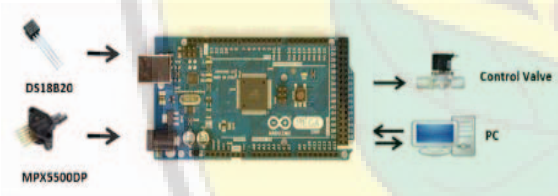

Fig. 2. Hardware system block diagram

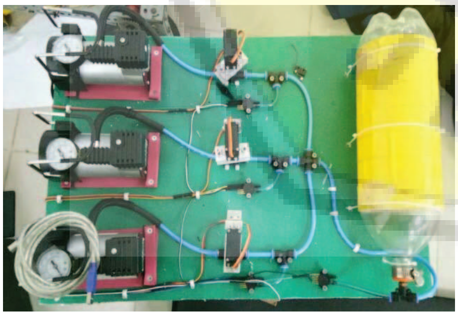

Fig. 3. Designing Hardware

In principle, the mechanical design to be made is a prototype of a plant air receiver system consists of 3 compressors, 1 container tube and supporting components of an electronic set. The compressor is using a 12 VDC mini air compressor with a 5-bar air pressure, a tube using a bottle with a maximum capacity of 9-bar.

C. Application of Extreme Learning Machine

Feed Forward Neural Network has been used based on its reliability. Conventional Neural Networks will usually be slower. It can take several hours, even more for training the data [19]. Unlike conventional methods, hidden neurons of the Extreme Learning Machine can use random numbers such as input weight and bias weight [20].

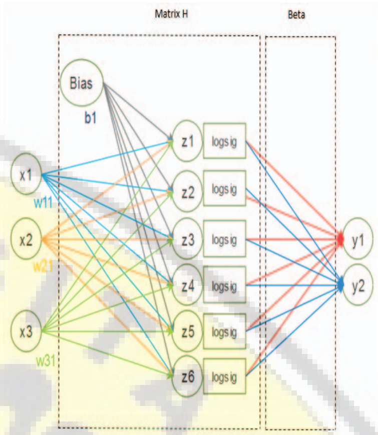

Fig. 4. ELM Structure

From Figure 4, there are 3 inputs marked with x1, x2, and x3 and a bias, there is also a hidden layer marked with z1 to z6 and there are 2 outputs or targets.

TABLE I
ELM TRAINING DATA

Input			Output	
Container	**Compressor1**	**Compressor2**	**Valve1**	**Valve2**
0	0	0	1	1
0.33	0.33	0.33	0.8	0.8
0.5	0.5	0.5	0.6	0.6
0.67	0.67	0.67	0.4	0.4
0.84	0.84	0.84	0.2	0.2
1	1	1	0	0

Table I shows the relationship between the inputs and the outputs on the plant. The data will be processed in matlab software. Figure 5 and Figure 6 show the input and output on matlab and figure 8 as the Visual Basic Interface.

TABLE II
DATA FROM THREE INPUTS

Input1	Input2	Input3
0	0	0
0.33	0.33	0.33
0.5	0.5	0.5
0.67	0.67	0.67
0.84	0.84	0.84
1	1	1

TABLE IV
DATA FROM TWO OUTPUTS

Output1	Output2
1	1
0.8	0.8
0.6	0.6
0.4	0.4
0.2	0.2
0	0

The ELM method use the "H" matrix that contains the output data set of all neurons. To write the data can be done easily because in accordance with predefined input and output data.

$$H = \begin{bmatrix} \emptyset(w_1 x_1 + b_1) & \dots & \emptyset(w_L x_1 + b_L) \\ \vdots & \ddots & \vdots \\ \emptyset(w_1 x_N + b_1) & \dots & \emptyset(w_L x_N + b_L) \end{bmatrix}$$

Matrix form according to the H formula on matlab is like in the picture below.

TABLE V
DATA FROM H MATRIX

0.5498	0.4013	0.6682	0.7109	0.5300	0.5349
0.5742	0.3624	0.7037	0.7863	0.5756	0.5530
0.5866	0.3430	0.7211	0.8191	0.5987	0.5622
0.5989	0.3241	0.7379	0.8478	0.6213	0.5714
0.6111	0.3058	0.7540	0.8727	0.6435	0.5805
0.6225	0.2891	0.7685	0.8928	0.6637	0.5890

$$\beta = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \; T = \begin{bmatrix} T_1 \\ \vdots \\ T_L \end{bmatrix}$$

Matrix form according to the formula β in matlab is like in the picture below.

TABLE VI
BETA

	1	2
1	-5.6565e+04	-5.6565e+04
2	-5.8158e+03	-5.8158e+03
3	5.1165e+03	5.1165e+03
4	-582.7696	-582.7696
5	-383.0545	-383.0545
6	5.7267e+04	5.7267+04

w is the weight value of the input data. b representing a value bias which are connected to the each hidden neuron. Both of these weights are determined at random with a value between -1 and 1. Target of this method is to find the value of β, using the equation 1.

$$\beta = H^{\dagger} T \quad (1)$$

D. Application of Neural Network

Back-Propagation Neural Network is widely used in neural network engineering, because the ability of nonlinear mapping. Back-Propagation network is a Back-Propagation nerve network without feedback. Application of Neural Networks (NN) Control of neural networks from compressor air pressure has 3 inputs and 2 outputs such as the ELM method. There are 3 inputs, Container, Compressor1 and Compressor2. And there are two outputs, Valve 1 and valve 2. The steps of applying the neural network method are:

1. This paper use the back propagation neural network method.
2. Determine the maximum predicted and target output errors.
3. The training process is done by using matlab software.
4. Mean Square Error analysis.
5. Insert the weights into the microcontroller program.

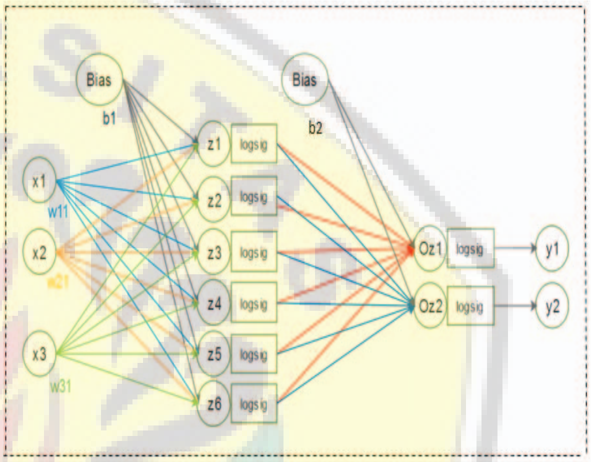

Fig. 7. Neuron Architecture of Neural Network

Figure 7 shows the neuron architecture with 3 inputs from the sensor, there are 2 hidden layers that have 5 neurons for each, and 2 outputs. The amount of data used to train is 6 data , then the data goes through the normalization process before going to matlab software. For the normalization process, we can see the formula below [8].

$$v' = \frac{v - \min}{\max - \min}(new \max - new \min) + new \min$$

TABLE VII
NN TRAINING DATA

Container	Compressor1	Compressor2	Valve1	Valve2
0	0	0	1	1
0.33	0.33	0.33	0.8	0.8
0.5	0.5	0.5	0.6	0.6
0.67	0.67	0.67	0.4	0.4
0.84	0.84	0.84	0.2	0.2
1	1	1	0	0

Table VII shows the relationship between input and output of the tool. The next process can be done by placing each weight on each layer into the program in the microcontroller.

Here is the result of the Neural Network training process using MATLAB.

The training process begins by using MATLAB software to get the best model based on training data. Figure 6 Shows the Mean Square Error result is stopped at 35 iterations. It means that the best training performance is reached at 7,0782e x 10-6 better than the maximum error (1 x 10-5) that have been set before.

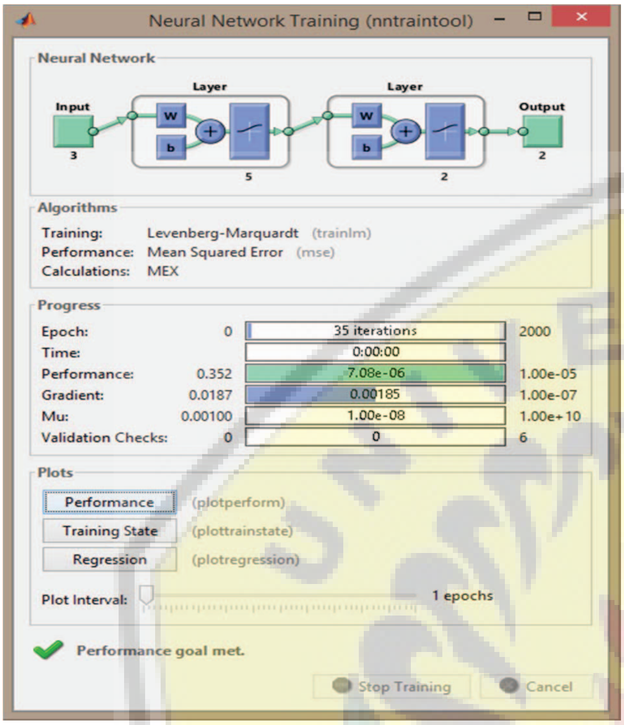

Fig. 8. Visual Basic Interface

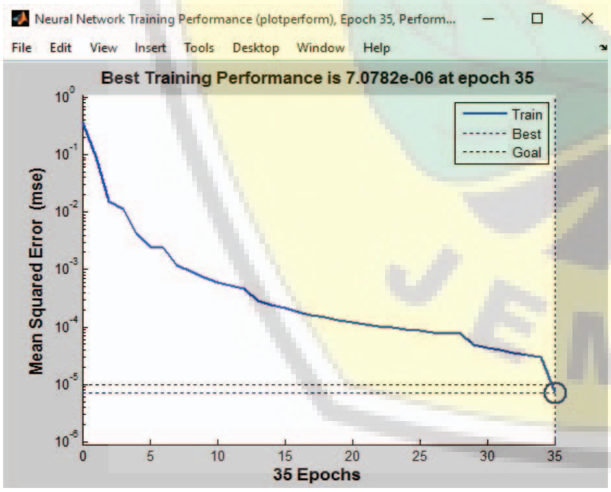

Fig. 9. Mean Squared Error

The training process begins with using MATLAB software to get the best model based on training data, fig 8 and 9.

Interface in this paper is using visual studio 2013. This interface is used for calculation method of Extreme Learning machine and Neural Network as well as a monitor function. microcontroller will send sensor data to visual studio and visual studio will do the calculation and send the output result to microcontroller to drive the servo motor. The used components are buttons, textboxes, labels, HScrollBar, frames and timers.

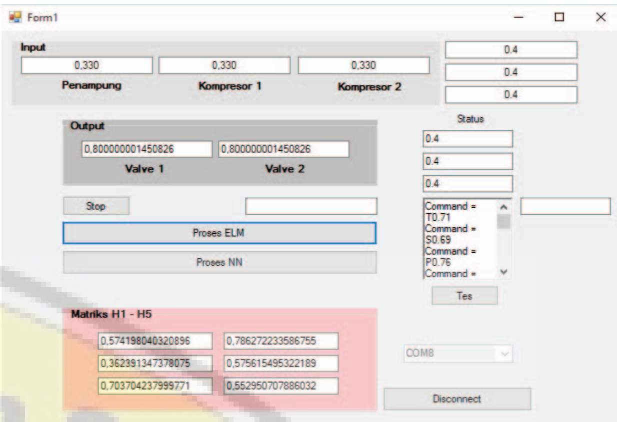

Fig. 10. Visual Basic Interface

III. RESULT AND DISCUSSION

TABLE VIII
ELM TRAINING RESULT

Input1	Input2	Input3	Valve1	Valve2
0.333	0.333	0.333	0,796603926	0,796603926
0.331	0.333	0.333	0,75135608	0,75135608
0.334	0.334	0.334	0,795469803	0,795469803
0.330	0.330	0.330	0,800000001	0,800000001
0.331	0.330	0.330	0,822641084	0,822641084
0.332	0.330	0.330	0,845163005	0,845163005
0.321	0.333	0.333	0,845163005	0,845163005
0.330	0.330	0.330	0,800000001	0,800000001
0.500	0.500	0.500	0,600000001	0,600000001
0.501	0.500	0.500	0,611337731	0,611337731
0.502	0.500	0.500	0,622551018	0,622551018
0.503	0.500	0.500	0,633639821	0,633639821
0.504	0.500	0.500	0,644604098	0,644604098
0.505	0.500	0.504	6,569730727	6,569730727
0.670	0.670	0.670	0,400000001	0,400000001
0.671	0.671	0.671	0,398834224	0,398834224
0.672	0.670	0.670	0,399097868	0,399097868
0.673	0.670	0.670	0,398453525	0,398453525
0.674	0.670	0.670	0,39768029	0,39768029
0.675	0.670	0.670	0,396778129	0,396778129
0.841	0.841	0.841	0,19879786	0,19879786
0.842	0.840	0.840	0,174895841	0,174895841
0.843	0.840	0.840	0,162145735	0,162145735
0.844	0.840	0.840	0,149263584	0,149263584
0.845	0.840	0.840	0,136249368	0,136249368
0.846	0.840	0.840	0,123103066	0,123103066

After done running on Matlab software then got the result from both used method. The Extreme Learning Machine method and the Neural Network method are successfully trained and applied in the plant when the resulting value of the actuator is almost the same as the reference value manually by using the valve rotation as measured by arc and resulting in a slight error. Errors can also occur because the input weight value (w) and bias (b) are not correct.

The values in table IX and table I was different, that is because there is a difference in value or difference between the actuator and the reference value and it is called an error. Actual data errors on each actuator are calculated and will be shown in table X.

TABLE IX
ELM TRAINING ERROR VALVE1 AND VALVE 2

Valve1 dan valve 2(ref value)	Valve1 dan valve2 (Training value)	Error
1	1	0
0.8	0,800000001450826	1,81E-07
0.6	0,600000001468288	2,45E-07
0.4	0,400000001474837	3,69E-07
0.2	0,2000000015395	7,7E-07
0	0	0
average *error*		2,60755E-07

TABLE X
NN TRAINING RESULTS

Input			Output	
Container	**Compressor1**	**Compressor2**	**Valve1**	**Valve2**
0.333	0.333	0.333	0,798905	0,798781
0.331	0.333	0.333	0,803164	0,803061
0.334	0.334	0.334	0,79786	0,797739
0.330	0.330	0.330	0,80203	0,801895
0.331	0.330	0.330	0,799901	0,799755
0.332	0.330	0.330	0,797757	0,7976
0.321	0.333	0.333	0,823546	0,823541
0.330	0.330	0.330	0,80203	0,801895
0.500	0.500	0.500	0,603756	0,603469
0.501	0.500	0.500	0,600915	0,600616
0.502	0.500	0.500	0,598075	0,597763
0.503	0.500	0.500	0,595235	0,594911
0.504	0.500	0.500	0,592395	0,592059
0.505	0.500	0.504	0,600958	0,600661
0.670	0.670	0.670	0,403612	0,40365
0.671	0.671	0.671	0,402523	0,402571
0.672	0.670	0.670	0,39905	0,399073
0.673	0.670	0.670	0,396788	0,396804
0.674	0.670	0.670	0,394538	0,394547
0.675	0.670	0.670	0,392301	0,392303
0.841	0.841	0.841	0,198066	0,1989
0.842	0.840	0.840	0,197456	0,198346
0.843	0.840	0.840	0,196378	0,19728
0.844	0.840	0.840	0,195309	0,196224
0.845	0.840	0.840	0,19425	0,195176
0.846	0.840	0.840	0,193199	0,194138

The values in table X and table VII are also be different, because there is a gap between the actuator and the reference value. Actual data errors on each actuator are calculated and shown in table X.

TABLE XI
NN TRAINING ERROR VALVE 1 DAN VALVE 2

Valve1 dan Valve2 (Ref value)	Valve1 dan Valve2 (Training value)	Error
1	1	0
0.8	0,802029642243232	0,253705
0.6	0,603755896764694	0,625983
0.4	0,403612064011319	0,903016
0.2	0,200504983494762	0,252492
0	0	0
average *error*		0,339199304

IV. CONCLUSION

In this paper has compared 2 methods of Extreme Learning Machine and Neural Network. We performed data testing on valve 1 and valve 2 using the two methods. Input data is done by using visual basic software or the data readings from MPX5500DP sensor. Errors can also occur because nput weight values (w) and bias (b) are not correct. Valve 1 and valve 2 are working effectively by using Extreme Learning Machine method than Neural Network because the generated average error training valve 1 and valve 2 using Extreme Learning Machine method is 2.60755E-07 and the average error generated training valve 1 And valve 2 using the Neural Network method is 0.339199304. So it can be concluded the Extreme Learning Machine method is much better than Neural Network because the average error of Extreme Learning Machine is smaller than the average error in the Neural Network method.

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