VOL. 17, NO. 13, JULY 2022 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

NEURAL NETWORK CONTROL DESIGN FOR AN AIR PRESSURE SYSTEM

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ABSTRACT

In this article, the control of a pilot pressure plant was developed by means of artificial neural networks, using the training and learning possibilities that these provide. The same control algorithms used in industrial plants can be applied in this pilot plant. With the implementation of this pilot pressure plant, a comparison was made between conventional control techniques and intelligent control in terms of efficiency and usefulness. This comparison was carried out by means of experimental data considering the results obtained with the conventional controller and the controller proposed by neural networks. A series of perturbations were performed once the system was in its steady state to obtain the response times of both control methods and determine the efficiency and advantages of intelligent control. The control was performed on the Arduino Mega board in serial communication with Matlab®(R2021b) to visualize the variables and thus observe the system behavior in real time.

Keywords: intelligent control, soft computing, modeling and simulation, artificial neural networks, pressure pilot plant.

INTRODUCTION

The use of intelligent systems is uncommon, it is not widely known because it is a science that is in continuous development. Because of this it becomes a challenge to investigate in this area. Hence the idea of exposing the techniques of intelligent systems through the control of an air pressure pilot plant using artificial neural networks to compare the performance of both conventional control and intelligent control and the importance of these methods to improve the performance of industrial processes and thus facilitate the use of these technologies in addition to creating new experiences for the advancement of science and technology in the service of industry.

The pressure pilot plant for control purposes (see Figure-1) is composed of a series of pneumatic, electronic, and electro-pneumatic devices connected among them, in order to simulate the dynamic interaction of a large industrial plant. The module is versatile since it is designed to apply different control techniques to achieve an adequate air pressure regulation.

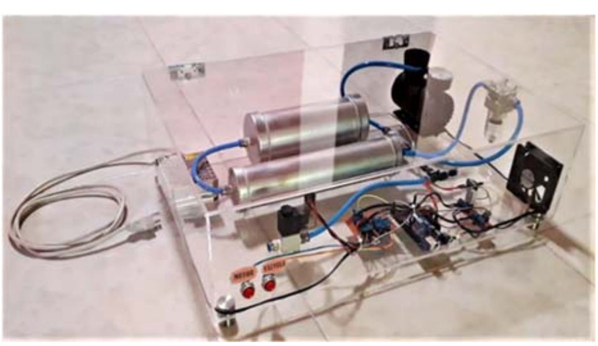

Figure-1. Pilot plant schematic view.

According to Figure-1, this pilot plant has the characteristic of being modular, since it can be modified both hardware and software for the purpose of programming and implementing advanced control techniques, where the information acquired from the measurement of the variables of interest through an embedded system can be taken to any software (either free or licensed) through serial communication, and thus use the software that is considered appropriate for the implementation of the control strategy to be studied. For the case proposed in this article, the main program in which the implementation and validation were carried out was Matlab®(R2021b), through the design of a friendly graphical interface, intuitive to use and easy to access, providing the user a convenience to enter parameters and visualize results in real time.

Embedded systems, although not very well named, are in many places, from vehicles to cell phones and even in some common household appliances such as refrigerators and microwave ovens. This is nothing more than a microprocessor that includes input/output interfaces on the same chip. Normally these systems have an external interface to monitor the status and make a system diagnosis[1]–[4]. Among the scopes that can be achieved with this type of systems are the following: Identify advanced control techniques applied in real processes, investigating the current methodologies that are being studied; implement control by means of neural networks to different systems, taking into account the variables to manipulate and the data collected; validate with experimental data in real time the results obtained with the neural network control against using a PID controller to confirm if there is a significant decrease in error and general improvements in the automatic control of processes, and encourage research and learning of neural networks for use in different areas of knowledge.

Artificial neural networks arise within the field of artificial intelligence, simulating the behavior of a biological neural network, in order to solve complex problems that would be very difficult to solve using conventional algorithms[5]–[8]. There are many different types of artificial neural networks, which are used for different applications depending on their development. These networks are widely used for tasks such as: data classification, pattern detection, obtaining models of the retina of the eye and brain function, probability assessment, optimization, computer vision, among others.

However, in the field of modeling systems for automation and control (automated robots, sensors in general, controllers, etc.), artificial neural networks are relatively recent, but their use is increasing in this type of systems due to the efficiency of the results that they can generate, avoiding the implementation of complex calculations with better performance. Currently, the control systems by means of artificial neural networks can be summarized in four structures: i) supervised control: the neural network learns a set of inputs and the desired outputs to solve the problem[1], [9]-[11], ii) direct inverse control: the neural network learns from the feedback of a system, so that, when the signal is obtained, it determines the control to be performed[12]-[16], iii) utility backpropagation: this structure optimizes the mathematical equation that represents the system, where its main disadvantage is that it requires a model of the system to be controlled[17]–[21] and iv) adaptive critical control: similar to the utility backpropagation structure, but without the need for a model of the plant[22]-[24].

Different researches can be found regarding the application of artificial neural networks in the field of control systems[25], [26], to provide autonomous failure detection capability for Mars exploration robots, in the aerial transport of a wire suspended load using drones, obtaining optimal parameters for neuron connection weights in multivariable control strategies, to carry out process identification and modeling techniques and control design of dynamical systems, for detection and diagnosis of faults in an industrial process, among many others.

Based on the above, in the industrial sector the design of control systems based on plant model can become complex due to the large number of variables and phenomena involved, intelligent control systems can contribute to the optimization and improvement of processes quickly, since they do not require a rigorous mathematical model of the process, can be fed with data sent by sensors and build efficient algorithms that achieve process optimization, improving their performance and quality in the final product to be produced. That is why in this article we intend to control a pilot pressure plant by implementing neural networks in order to make comparisons in real time with conventional PID control using experimental data; taking into account the variables to be manipulated and the data collected to show a significant decrease in error and general improvements in the current automatic control of industrial plants.

The rest of the paper is organized as follows: section two presents the methodology considered for the development of this study through the neural networks model; section three presents the description of different control analysis through discussion of the results obtained; finally, section four presents the conclusions and future work derived from this research.

RESEARCH METHOD

The neural network method was selected because of its great capacity to adapt to different types of problems, the previous experience with the use of neural networks[4], [25]-[27], and the ease of implementation of this type of technique, in addition to being a technique with great potential that is causing a revolution by proving to be the future of technology.

An artificial neural network (ANN) is an automatic learning and processing paradigm inspired by the functioning of the human nervous system[3], [13], [14], [21]-[23]. A neural network is composed of a set of neurons interconnected by links, where each neuron takes as inputs the outputs of the preceding neurons, multiplies each of these inputs by a weight and, by means of an activation function, calculates an output. This output is in turn the input of the neuron it precedes. The union of all these interconnected neurons is what makes up the artificial neural network [7]-[10].

The artificial neural network as well as biological networks learn by repetition, and the more data you have to train and the more times you train the network the better results you will get[18], [19], [23]. Training an ANN is a process that modifies the value of the weights associated with each neuron, so that the ANN can generate an output from the data presented in the input[6]. The weights are really the way the neuron learns. These weights will be modified in a certain way to adapt the value of the output in such a way as to minimize its error with respect to the real result that the artificial neuron should produce[10], [16].

Based on the above arguments, the following questions arise for this methodological development: What data are of vital importance for the management of the problem to be addressed?, which variables are relevant to address and manage this problem?, where can the data be obtained?, how to prepare and encode the data?, what type of network should be chosen?, how many hidden layers and how many neurons are necessary to manage the possible solution to the proposed problem?, what learning rule to choose?, and what initialization is given to the weights?. For this specific project, an in-depth analysis of the process is required to obtain the mathematical function of the process and all the variables that influence the problem to be addressed. These data will be acquired by means of experimental tests using the pilot plant of the pressure variable. The data obtained from the experimental tests will be organized in a spreadsheet to be later entered into the software that will be used to code the neural network (Matlab®(R2021b)). The network to be designed will be initially selected with a configuration of 2 hidden layers with 20 neurons in each layer, 2 inputs, 2 outputs and a learning coefficient of 0.3 and random weights. However,

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once implemented, several tests will be performed to determine if a change in any of the parameters is necessary to obtain better results. The structure intended to be implemented for this project is shown in Figure-2. It is proposed to use the neural network as the overall control system, and the possibility of switching between the network and the conventional PID will be explored. This structure has the possibility of being changed if a better alternative is discovered in the future during the process of development, research, and implementation of advanced control systems.

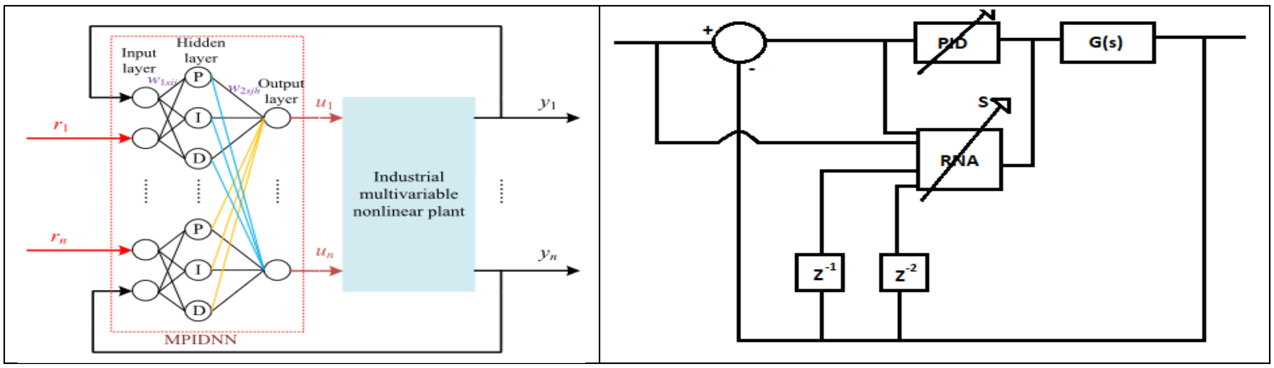

Figure-2. Proposed ANN scheme for intelligent control.

Initially the ANN will be trained by entering the values obtained from preliminary tests, in addition to the expected values, performing training cycles as necessary until the network has an allowable error. Now, after providing a solution to each proposed question, the comparison of an intelligent automatic control system using neural network techniques and its advantages over the conventional control system are raised, with which is possible to have a better response time, greater accuracy based on the data obtained against the possibility of obtaining improvements in error, greater efficiency in the control against conventional control, cost, and utility. Faster and more efficient control could mean a higher rate of profit for the industries in which it is implemented, in addition to providing a reliable and safe solution in processes that require high precision, in addition to promoting the use and expanding the existing documentation on this type of techniques applied to process control.

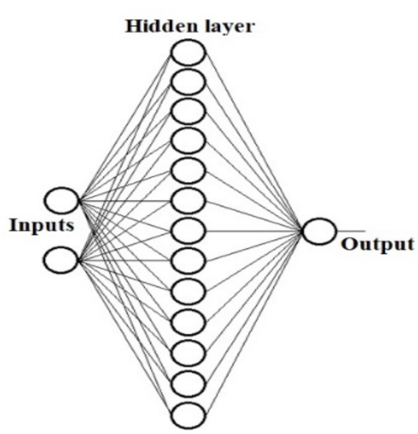

Figure-3. Neural network configuration for intelligent control.

On the other hand, an interface was designed in which other types of neural network topologies different from the proposed one could be configured in order to have different options in the future. This makes it easier to perform tests with different configurations, for example, a neural network with 1 hidden layer of 13 neurons, 2 inputs, 1 output and a learning coefficient of 0.01 can also be configured (see Figure-3).

A first test of the pilot pressure plant was carried out with the algorithm using conventional control, evaluating the state of its components and the operation of the program used to perform the PID control. No major changes were made to the structure or operation of the plant, so the operation mode and its mathematical function remained unchanged.

As regards the activation functions, several functions were tested, among them the logsig, the ReLu, the softplus, the hardlim and the tansig, choosing in the end the logsig since it is the function that reaches a low margin of error in the shortest time for this specific process with the input data obtained. The problem of overfitting can be defined as an excess of complexity of the neural network that can be detrimental to it, it was taken into account due to the difference in the nature of the data needed to drive the final control elements (the valve and the air compressor motor of the pilot plant).

Finally, it should be noted that the neural network was developed with its own code (the Matlab library was not used) along with the database with which it would be trained, the Arduino program was implemented to perform a serial communication between the user interface and the device that directly manages the sensors and actuators of the pressure plant. The Matlab program consists of 4 parts: i) Neural Control: This is the main part, where the neural network is configured and trained. This was done using arrays of cells, so that it was possible to store arrays of different sizes in a single variable. Each row of the network variable is a different type of data, such as the weights of

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each layer, biases, errors, and so on, ii) Feedforward: In this file the forward propagation stage of the network was performed, where all the elements of the database are passed through the neural network, obtaining an output, iii) Backpropagation: The backpropagation algorithm implemented for this network was gradient descent, where the aim is to minimize the error by calculating the partial derivatives of the error or cost function (mean squared error in this case), in terms of the weights of each neuron, modifying them in order to reduce the error in the output, and iv) Operation: This part of the program is responsible for performing the communication between the Arduino and Matlab via serial communication once the network has been trained. It is a cycle in which the Arduino indicates to Matlab the value obtained by the pressure sensor, which uses the Matlab program together with the setpoint established as inputs of the neural network already trained, and based on the output of the network, tells the Arduino how to proceed (activate or deactivate the air compressor motor, as well as the valve).

Several tests were performed to verify the learning of this network and that the data delivered by it were consistent even with parameters that it had not received in the training stage, obtaining more than acceptable values, and thus proceeding to the implementation stage.

When running the program, the user will be presented with the initial screen (see Figure-4), in which the parameters are entered to configure the desired neural network and proceed with its training. From Figure-4 and once all the parameters have been set, press the "train" button, which will immediately change to "stop", and the graph will show how the error varies with respect to the passing of the epochs (see Figure-4a).

Figure-4. Main screen, a) Training view, b) Main program view loading the selected configuration, c) initial screen view saving the configuration, and d) Operation screen in communication with the module.

If the stop button is pressed, the parameters of the learning coefficient, maximum desired error, and maximum number of epochs can be modified to continue the training from where it was left off, and variable learning coefficients

 ISSN 1819-6608
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can be configured. If you wish to restart a neural network from scratch, just click on the reset button and enter the desired values again to configure the new network. The last option offered by this interface is the load configuration button, with which a previously obtained neural network can be loaded into the program, either to continue configuring it or to work directly on it (see Figure-4b). Once the training is finished, the program will ask if you want to save the configuration for later use, and if you answer yes, a box will open to choose the location and name to save the dataset (see Figure-4c). Once the learning and training process has been completed, it will automatically go to the operation screen, from which the pilot plant will be controlled with the trained network (see Figure-4d). This screen contains only 2 fields: i) COM Port: Port where the Arduino is connected. This can be seen in the device manager, in the COM ports section, looking for the one with the word Arduino. Once the port is entered, press the "connect" button, which will start the communication between the Arduino and the user interface, showing in real time on the graph the value measured by the pressure sensor. The text of the button will change to "disconnect", which will terminate the connection with the module, and ii) Setpoint: Percentage of pressure to which you want to bring the system. (For example, if 10% is desired, enter 10). Each time the setpoint value is changed, the send button must be pressed so that the instruction is sent to the Arduino and the control is performed. The "back" button is used to return to the training screen.

RESULTS AND DISCUSSION

The main results of the intelligent control implementation are shown below, where the final neural network control scheme is shown in Figure-5.

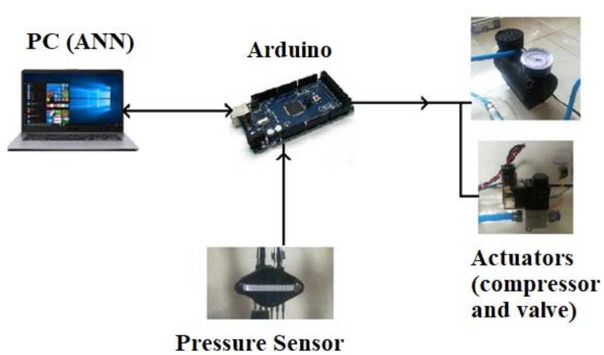

Figure-5. Control scheme with ANN and communication between devices.

The neural network was trained from plant data, using the dataset “motor.txt” and “valve.txt”, both of which have 500 rows of data, the first column being the sensor value, the second the setpoint and the third the value at which the valve or compressor motor should be set (between 0 (0%) and 1 (100%)). Tables 1 and 2 shows a portion of the recorded data.

Table-1. Dataset “valve.txt” used to train the network.

Sensor value (%)	Setpoint (%)	Valve opening
0	0	0
2	0	1
1	0	0
50	50	0
52	50	1
100	98	1
98	100	0

Table-2. Dataset “motor.txt” used to train the network.

Sensor value (%)	Setpoint (%)	Motor speed
0	0	0
0	10	0.810050251
0	20	0.831155779
10	0	0
10	10	0
10	20	0.810050251
10	30	0.831155779

These datasets were used to train the network with different configurations. After obtaining the trained neural network and implementing it in the pilot plant, several tests were performed comparing the conventional control program with the intelligent control program, obtaining the results shown in Figure-6.

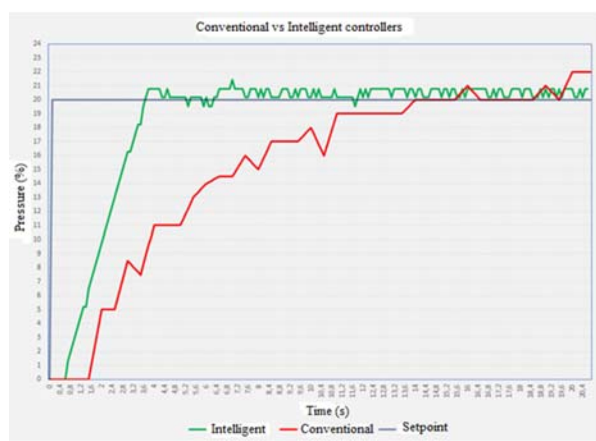

Figure-6. Comparison results between the two control strategies.

To compare the two control strategies, both programs were given a setpoint of 20% for the pressure variable. Figure-6 shows that the intelligent control (in green) has a better response time than the conventional control (in red), in addition to reaching the indicated point in a shorter time (3.6s vs. 14s respectively).

VOL. 17, NO. 13, JULY 2022 ISSN 1819-6608
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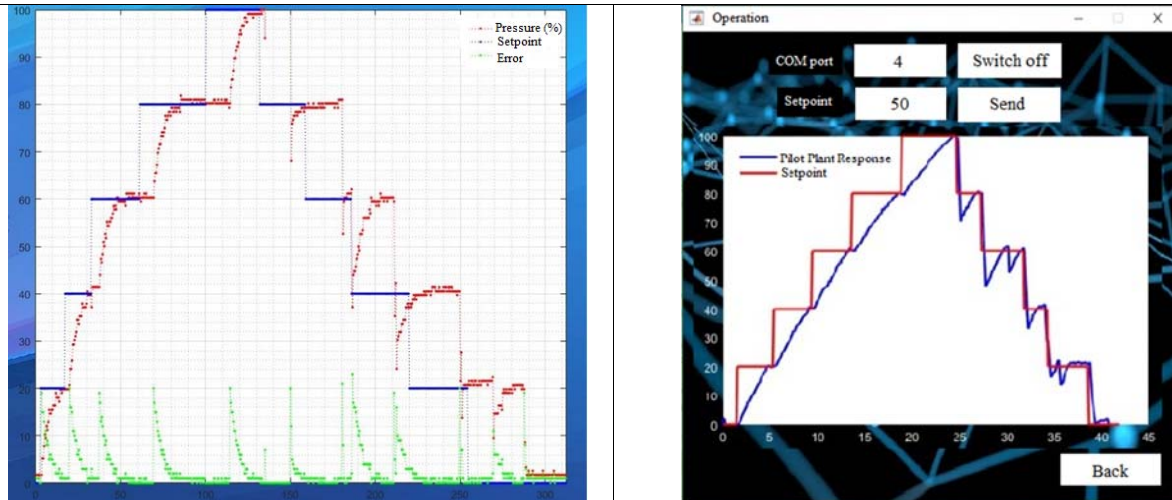
With this in consideration, further comparisons were made using the programs implemented for each type of control strategy, the first of which was an upward step change, increasing 20% each time in both programs until reaching 100%, and decreasing again 20% until reaching zero (see Figure-7). Figure-7a shows that the steps were started from the beginning (t=0 s) and increased each time the program reached the setpoint, taking 290 seconds to complete the entire run. With the intelligent control, it started at 2 seconds, completing the whole process at 40 seconds, thus obtaining a total time of 38 seconds, being in this test the neural network control 7.6 times faster than the conventional control (see Figure-7b).

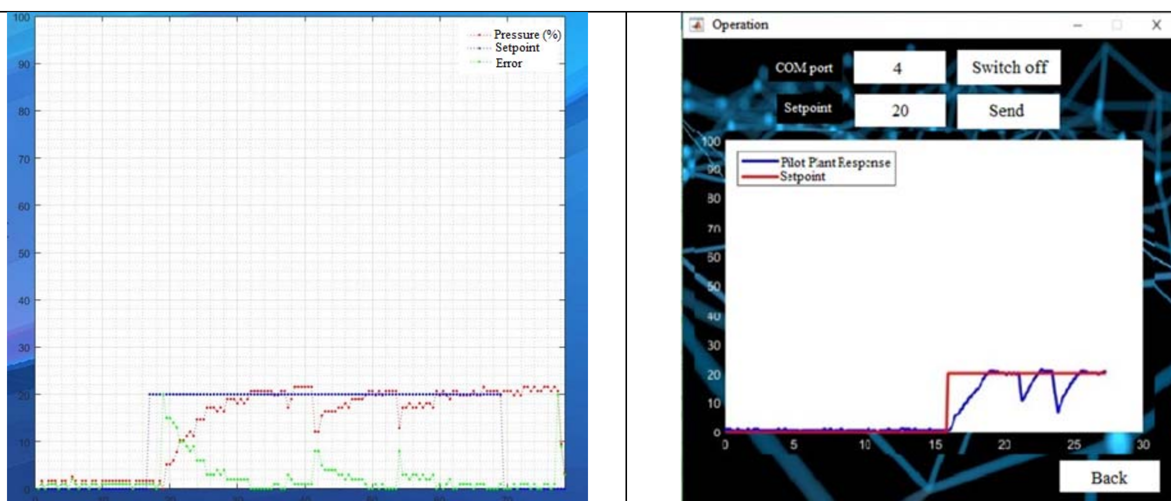


a) b)

Figure-7. Pilot plant response to a step change of 20%, a) Conventional control, and b) Intelligent control.

A final validation of both control algorithms was performed to observe their behavior under a disturbance of the air inlet valve, this test was developed once the pressure variable has reached its steady state value (setpoint).

Figure-8 shows that both control strategies adequately compensate this disturbance, returning the pressure variable to its setpoint; however, the neural control strategy manages to bring the variable to the control point in half the time.



a) b)

Figure-8. Plant response to disturbance, a) Conventional control, and b) Intelligent control.

CONCLUSIONS

A pilot pressure plant was controlled by means of neural networks, comparing conventional control with intelligent control. It was identified that advanced control techniques by means of artificial intelligence applications can become more efficient than the conventional techniques still used in the process industry.

The Intelligent control techniques applied in real processes guarantee an adequate regulation and optimization of highly dynamic processes, since the expected results can be obtained in a shorter time without the need to use complex mathematical models, which are often difficult to obtain, or the phenomena involved in most of them cannot be understood in depth.

With the implementation of this type of advanced control strategy, there was a significant reduction in the error when comparing the conventional control data against the control data using neural networks and, in turn, a better response time to disturbances was evidenced. Taking into account the results obtained, it can be affirmed that neural networks can be the pillar of the so-called fourth industrial revolution, proving to be useful in multiple fields, offering high efficiency and reliability in the automatic control of industrial processes.

ACKNOWLEDGMENTS

This research did not receive any kind of funding from any entity or organization and does not have any conflict of interest regarding this investigation.

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