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Comparative Study Between A Neural Network Controller And A Classic Pi Applied To An Experimental Hydraulic System

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ABSTRACT

A large part of the industrial processes, when entering competitiveness, must be subject to flexibility so that related aspects can be adapted according to demands at the production level as well as current technological trends. One strategy to appropriate these processes is to adapt the use of control techniques such as Artificial Neural Networks (ANN) inspired by the biological neural networks of the human brain; its advantage is the ability to provide and abstract dynamic features from a series of experimental data. Under this concept, an ANN controller system applied to a test hydraulic system was developed, which was compared with a classic PI strategy. Said
comparison at the simulation level presented satisfactory results, demonstrating the quality and optimization in the processing, emulation and control of a physical system with non-linear characteristics. The performance of the networks is noteworthy, the Tau response times for both controllers when the level of the tank decreases are similar, however the settling time of the neural network was between 20% and 40% faster than the controller PI. Presence of overshoot above 20% was identified by the PI control in response to changes in the setpoint for the size of the tank level.

Keywords— Neural networks, PI, control, hydraulic.

1. INTRODUCTION

From the importance and influence in relation to the quality of technology in the industry, the use of embedded simulation level systems that have as a function more complex tasks to human perception has been highlighted [1], therefore, quality is required to understand the control of physical variables at a dynamic level. Recent advances have allowed directing the efforts in the field of electronic control to solve, analyze and emulate high-precision dynamic characteristics. The industry over time has been the target of classical control methods such as PID, where no tolerance and the need for rapid stability are key study requirements for the control area. However, the challenges to linear and nonlinear systems require new alternatives that lead the solution to these challenges. An alternative solution is the provision of artificial neural networks, for our case study, applied to a hydraulic tank systems, whose purpose is to complement the shortcomings of classical control methods. This paper presents the results at the exploratory research level under a simulation and comparison of a new control method as an alternative resource to the classical control techniques applied to a vertical tank type nonlinear hydraulic system.

2. SMART CONTROL

The current demands of physical systems have generated the increased leverage of automation and control with a great diversity of functions other than the basic ones of task execution and process monitoring [2]. The Industry 4.0 trend is driving a series of techniques developed mainly at the level of artificial intelligence that seek to solve control problems that cannot be tackled by traditional methods [3]. The Industry 4.0 trend is driving a series of techniques developed mainly at the level of artificial intelligence that seek to solve control problems that cannot be tackled by traditional methods [4].

2.1 Neural Networks (NN)

Neural Networks is a technology developed in software and hardware, in which systems can be built that are capable of learning, adapting to different conditions, or predicting future states through databases. These techniques used are developed to face problems that are commonly solved by a human being and were difficult for machine logic systems. Their operation is based on a large amount of data in a parallel processing that interconnects each one. Neural networks are used for prediction, data mining, pattern recognition and adaptive control systems, see Figure 1. Also, they can be used with other tools such as statistics, algorithms, fuzzy logic, and others.[5].

Artificial neural networks have several definitions, some short and others explaining in detail, such as:

- A new form of computation, inspired by biological models.
- A mathematical model composed of a large number of procedural elements organized in levels.
- A computer system composed of a large number of simple, highly interconnected process elements, which process information using their dynamic state in response to external inputs.

- Artificial neural networks are massively parallel interconnected networks of simple (usually adaptive) and hierarchically organized elements, which attempt to interact with real-world objects in the same way as the biological nervous system does [6].

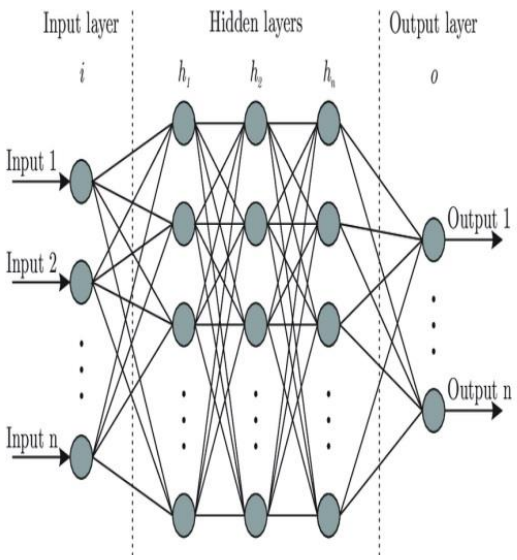

Fig. 1. Artificial Neural Network [7]

3. HYDRAULIC EXPERIMENTAL STUDY SYSTEM

The hydraulic system shown in Figure 2 is composed of a tank with a base radius of 19 [cm] and a maximum filling height of 45 [cm]. The variable height measured with an ultrasonic sensor and the liquid outlet is adjusted by a 1" proportional solenoid valve with a maximum flow area of 160 μm^2

which reaches the reservoir tank. For the inlet flow, a reservoir tank of approximately 200 [mL/sec] is provided using a hydraulic centrifugal pump and a ½" piping arrangement with manual valves to establish this inlet flow.

Fig. 2. Experimental hydraulic system

For the instrumentation of the tank, the characteristics of the hydraulic system were considered, emphasizing the use of electronic elements, such as a solenoid valve with arduino one auxiliary board, which with a potentiometer is in charge of giving the opening point, through a PWM signal amplified to 10 [V] by means of a L298N H-bridge module as shown in Figure 3..

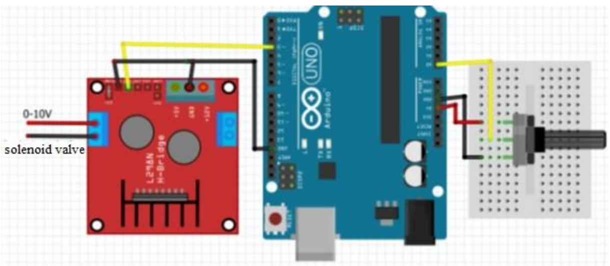

Fig. 3. arduino uno auxiliary circuit with L298N

3.1 Analytical model of the hydraulic tank system

For this system whose behavior is nonlinear, Figure 4, an inlet flow "Qin" was defined where it affects the opening "a1" of valve 1 to a cylindrical tank of height "h" and base area "A", as well as an outlet flow "Qout" where it affects the opening "a2" of valve 2.

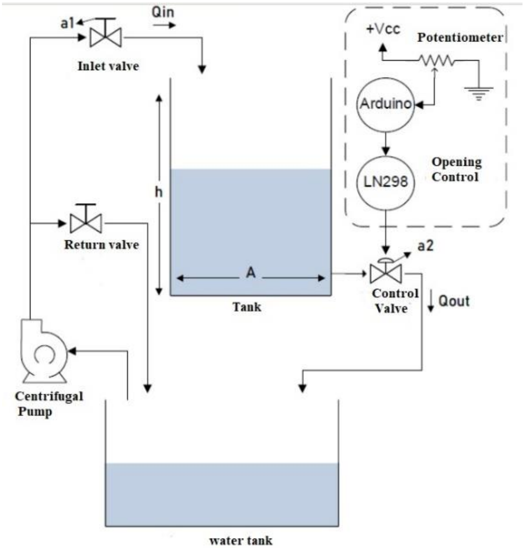

Fig. 4. Schematic diagram of the study hydraulic system

This system is represented by the variables in the liquid flow, where the amount of liquid stored in the cylindrical tank and the resistance at the outlet orifice will be equal to the inlet flow minus the outlet flow, the mass conservation principle, as shown in equation 1.

$$\text{Volumen} = \text{Area} * \text{height} = \text{input flow} - \text{output flow} \quad (1)$$

Assuming that the outflow from the tank has a non-linear behavior we arrive at equation 2, where "A" is the area of the base, "g" is gravity, "k" is a constant of the valve and "h" is the head.

$$A\frac{dh}{dt} = Q_{in} - Q_{out} = Q_{in} * a_1 - k * a_2 * \sqrt{2gh} \quad (2)$$

Under Taylor's linearization, the following equation presents the analytical transfer function, which will be used for the development of the controllers and subsequent studies.

$$G(s) = \frac{k\sqrt{2gh'}}{AS+C} \text{ donde } C = \frac{ka'_2\sqrt{2g}}{2\sqrt{h'}} \quad (3)$$

In view of the above, the requirements to be met by the instrumentation system were identified as follows:

- The signals to be received have amplitudes of 4-20 [mA] and 0-10 [V], using an analog instrumentation channel.
- The configuration given to the signal conditioning was oriented towards low range voltages and must have an analog/digital conversion for acquisition by the Raspberry Pi 3B+ development system (Patil & Bhole, 2019), whose analog pins handle logic levels between 0 and 3.3 [V].
- Data acquisition must be controlled in such a way that it is possible to pause and restart the data acquisition process.

With these requirements established and the characteristics of the Raspberry Pi 3B+, an instrumentation system was designed consisting of a conditioning stage and an analog/digital converter to deliver the signals to the board, as well as a graphical user interface for the visualization and storage of the experimental data. Figure 5 shows the simplified block diagram of the proposed instrumentation system.

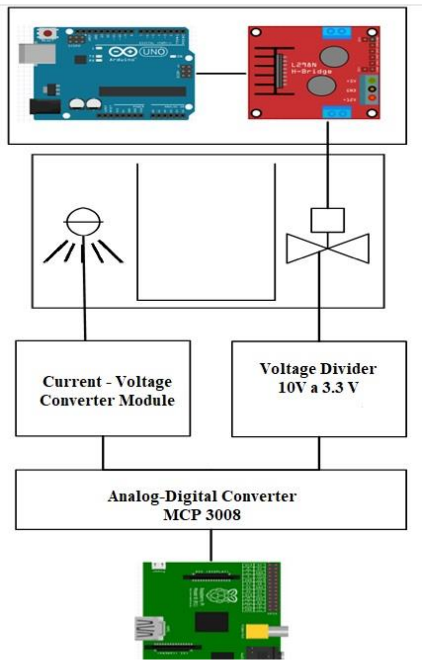

Fig. 5. Simplified block diagram of the developed instrumentation system

4. DESIGN OF THE CLASSICAL PI CONTROLLER AND NEURAL NETWORK CONTROLLER FOR THE HYDRAULIC SYSTEM

4.1 Classic PI controller

Having the transfer function product of the linearization, equation 3, we proceeded to the design of the classical PI controller, which has the characteristic of eliminating the error and its viability to respond to large disturbances such as pressure, flow, and liquid level. The pole assignment method was applied manually to solve the direct nonlinearity of the plant. The transfer function is presented in equation 4 as the modifiable or perturbed part of the plant, based on the block diagram shown below:

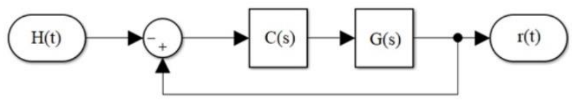

Fig. 6. Block diagram of the system to be controlled.

Where the block C(s) represents the controller and G(s) represents the plant. From the previous diagram, a transfer function was designed that allows having as an analysis objective the reduction of the accommodation time, with reductions in the order of 45%. The transfer function of the classical PI controller is presented in the equation 4 below.

$$C(S) = 1{,}416 * \frac{167{,}5*S+1}{167{,}5*S} \qquad (4)$$

4.2 Neural network controller

For the design of the neural network, the differential equation obtained in the modeling of the system was considered as the objective function. During the controller design process, a recurrent neural network structure was used, (see Figure 7), whose structure is defined for one input and one output, being the perturbed variable the opening and the variable to be controlled the height, respectively.

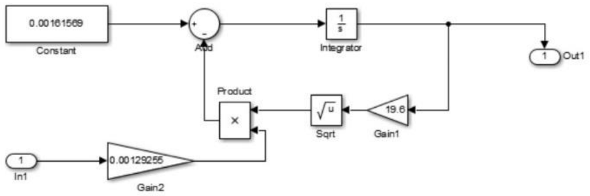

Fig. 7. Mathematical structure of the neural system.

Subsequently, a file was created containing the neural network to be used along with the system or plant to be controlled, shown in Figure 8.

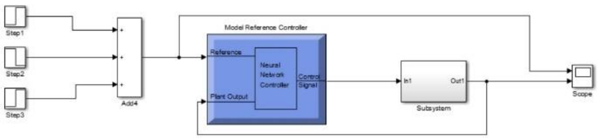

Fig. 8. Plant controlled by neural network.

Before training our controller neural network, a neural network was trained to copy the dynamics of the system, using the plant identification tool, to record the parameters of the neural network that would copy the dynamics of the plant. As a result of the training we can observe in Figure 9, the adaptability of the neural network found against the reference model of the plant against some perturbations in its input. As can be seen in Figure 10, the neural network took a portion of the plant data to perform a validation, having an input, performing the imitation and obtaining an output with a minimum error in the order of 0.5 x 10-5. Finally, the training data for the controller neural network was generated as shown in Figure 10.

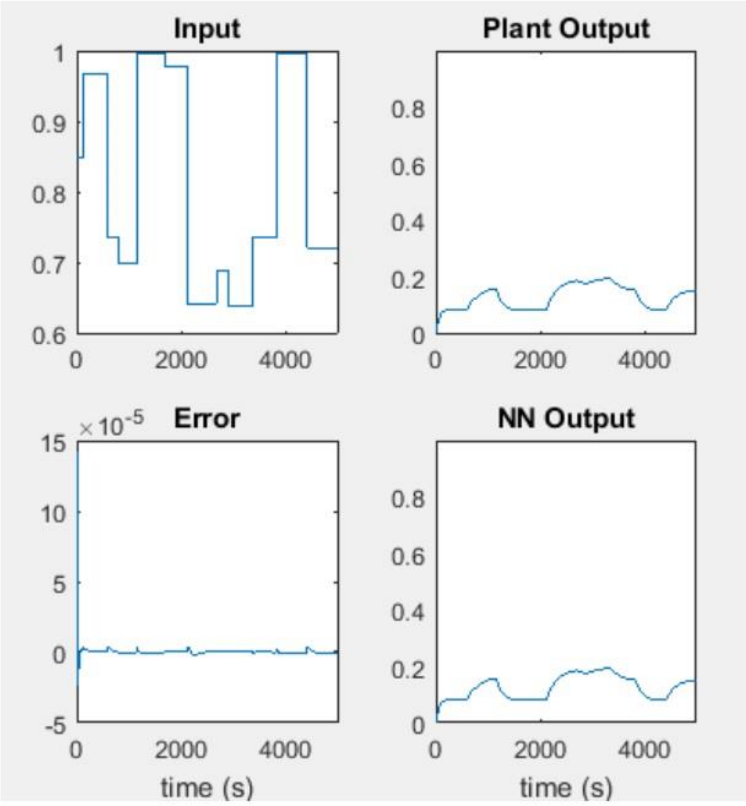

Fig. 9. Neural network response vs. plant model on training data

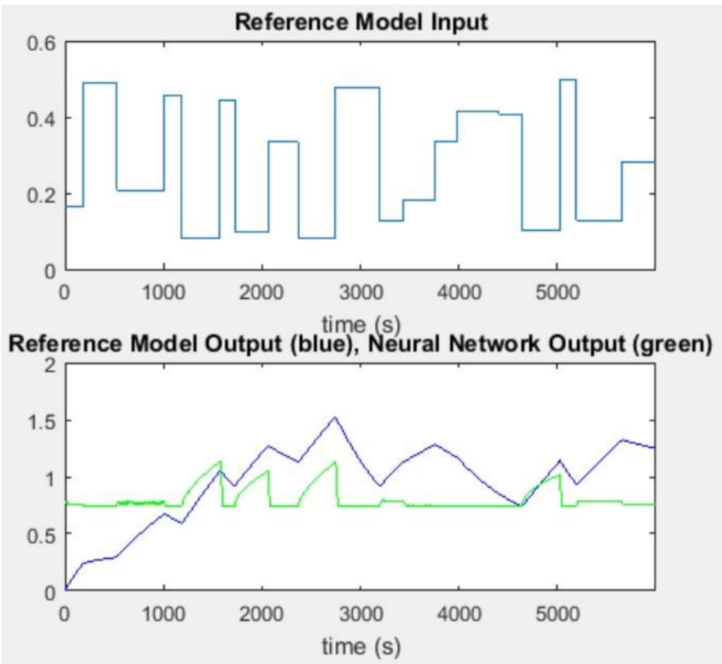

Fig. 10. Data generated for controller RN training

5. EXPERIMENTAL RESULTS

Simulations were performed for variations in the inflow and external disturbances to the hydraulic system, observing the behavior of the head and opening, as well as the response of the zero head to the equilibrium head of the system in an uncontrolled and controlled manner.

5.1 Variation of tank inlet flow with steps

Considering the model of the system previously obtained, the due simulation was executed to alter the inlet flow. This model was proposed under the effect of 6 perturbations, applied with a separation of 800 seconds between perturbations. For the first perturbation, the inlet flow is increased by 50%; in the second perturbation, the same proportion of the flow that was increased in the previous perturbation is decreased. In the third perturbation the flow is increased by 35%, for the fourth perturbation the reduction is made in the same proportion applied in the previous perturbation. In the fifth perturbation the flow was increased by 15%, and for the sixth perturbation the same proportion was reduced, reaching again the initial flow.

For the test of the neural network controller, a Matlab script similar to the one used for the testing of the classical PI controller was created. In this script, the tank constants already known in a past objective are specified and the times at which the moments of change in the reference for the simulation of the neural network controller are specified. Whose answers were exported from Matlab work, where the data were presented, showing the dynamics of the controlled tank, see Figure 12, under the effect of a neural network.

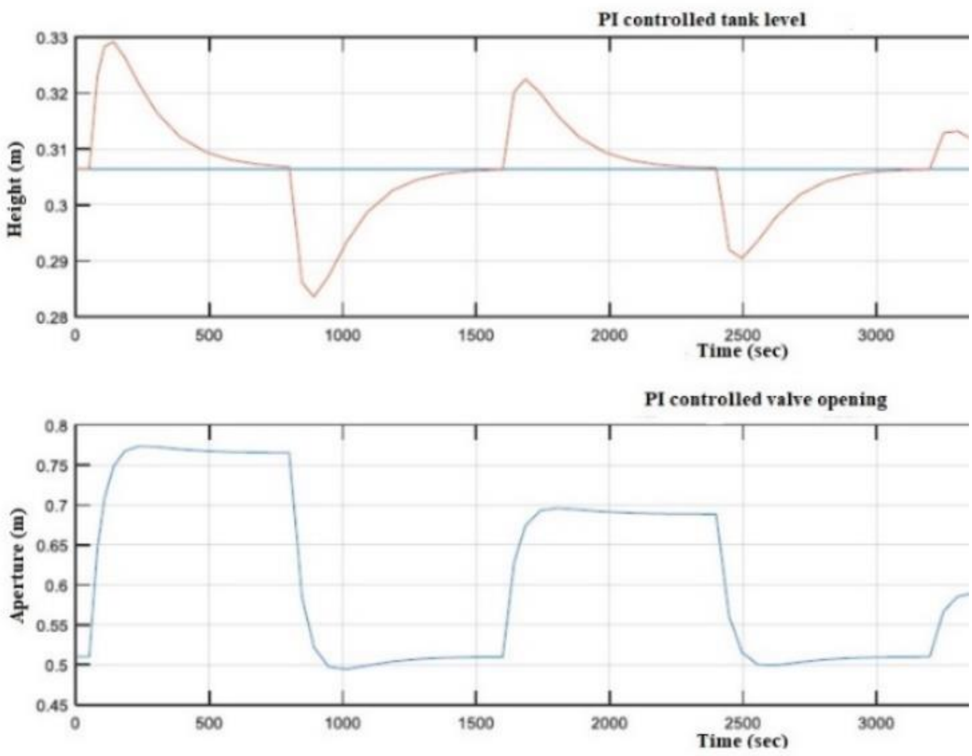

Fig. 11. PI controller response to perturbations in step input flow.

Considering the model of the system, the simulation, data acquisition and graph shown in Figure 13, under the effect of a neural network in the presence of 6 input disturbances in the input flow, are shown below.

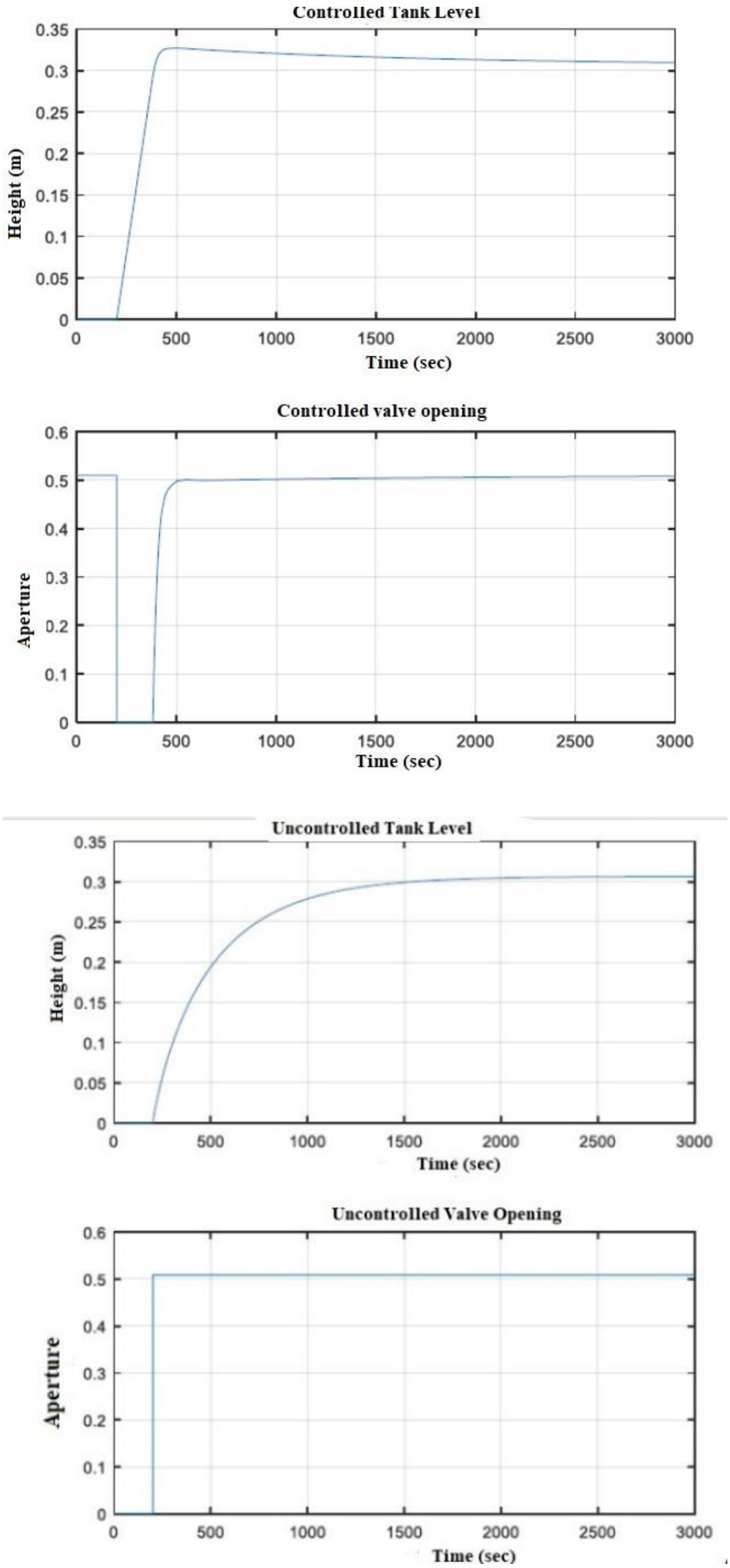

Fig. 12. Simulations of the controlled and uncontrolled system for a natural response from 0 to equilibrium point.

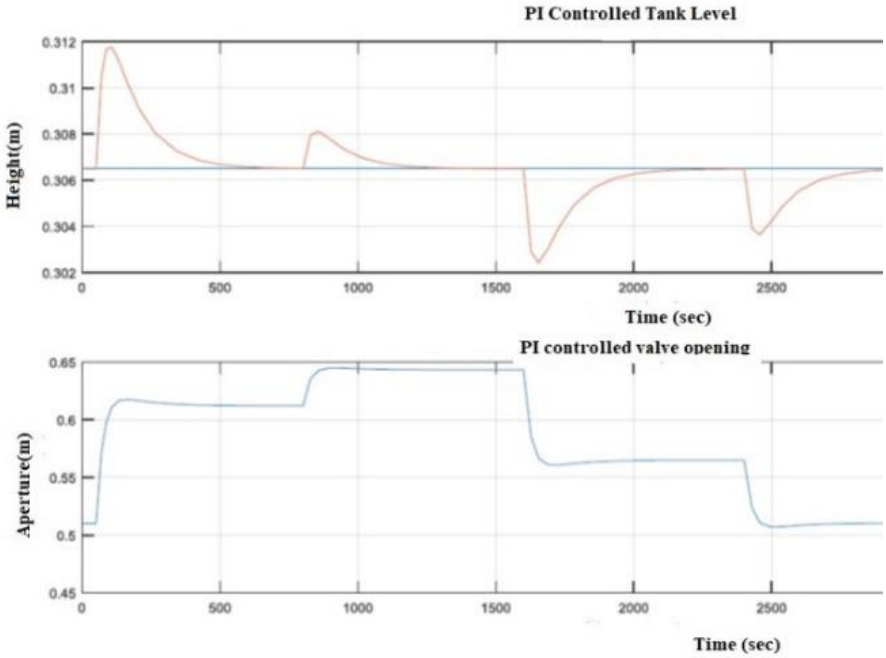

Fig. 13. RN controller response to disturbances in inlet flow by steps

5.2 Comparison of dynamics in controller responses.

Once the two controllers were obtained, they were compared, taking into account the following data to be evaluated:

- ✓ Time (Tau): time in which 63.2% of the final value is reached.
- ✓ tp (peak time): Time at which the maximum peak occurs.
- ✓ ts (settling time): time in which the signal reaches 98% of the final value.
- ✓ Mp (maximum overshoot): is the magnitude at which the first overshoot occurs at peak time.

Figure 14 shows both controllers and their perturbations, we can see that the neural controller is not the same as the PI level when a perturbation is performed; in fact, it is almost half, and its response times to return to the reference level are faster.

Figure 15 shows the behavior of the openings and it can be seen that the NN controller acts faster on the valve, not allowing the tank level to increase or decrease too much at that moment with respect to the reference level.

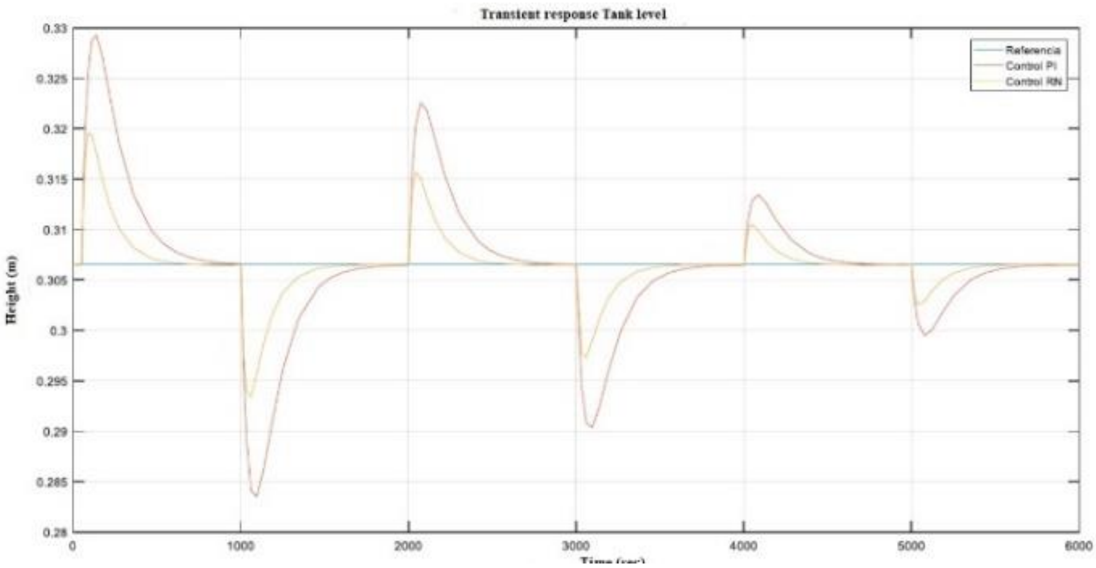

Fig. 14. Response from both controllers.

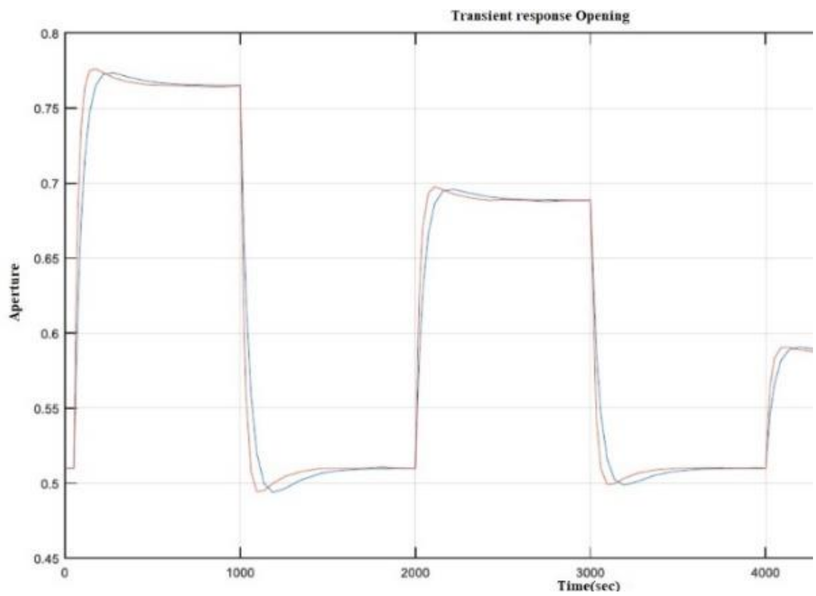

Fig. 15. Openness response in controllers

The neural network for +/-50% disturbances has a Tau 25% faster and a settling time Ts 34% faster than the PI controller. The neural network for +/-35% perturbations has a Tau 17.6% faster and a settling time Ts 30% faster than the PI controller. The neural network for +/-15% perturbations has a 25.5% faster Tau and 22% faster settling time Ts than the PI controller. No controller was shown to have MP spikes and overshoot. Positive disturbances tend to have longer response times than negative disturbances.

CONCLUSIONS

The analytical model obtained showed a system dynamics similar to that obtained empirically, with a difference in its Tau response time of approximately 8 seconds; however, its equilibrium level is higher by approximately 2 centimeters.

The Tau response times for both controllers as the tank level decreases are similar, however, the settling time of the Neural Network is between 20% and 40% faster than the PI controller.

When the liquid level is decreased, the Tau times for both controllers are similar. The difference occurs in the settling time, in which the neural network is between 60% and 78% faster depending on the distance interval between the reference point and the desired level, compared to the PI controller

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