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CONTROL BASED ON NEURAL NETWORKS TO A MULTIVARIABLE HYDRAULIC SYSTEM

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ABSTRACT

This work presents the control based on neural networks to a multivariable hydraulic system, developed in the MatLab software where is intended to control the level and the output flow of a tank by manipulating the voltages of the actuator, voltage pump and valve. Being a multivariable system, the Bristol method is applied for evaluating the interaction between the variables. The interface is performed in Simulink, which complies with the task of monitoring, control and visualization of the system in real time. Finally, the response of the neural controller in real time to different changes in the set-point of flow rate and level is evaluated. As a result, a good performance is shown, considering as parameters the steady state error and the settling time, but also completely eliminates the overshoot of the two variables controlled of the process.

Keywords: neural network controller, hydraulic system, inverse model, multivariable system, simulink.

1. INTRODUCTION

Current industrial processes are characterized by being non-linear and by showing more of a control loop, which makes them have a higher degree of complexity in its automation. These systems have generated interest in the use of different intelligent methods that are capable of exercising optimal controls. These processes are known as "Multivariable" are aimed to control more than one variable such as level and flow in the case of systems of coupled tanks.

Many studies have been done with regard to these systems, such as the analysis and application of adaptive control algorithms which were implemented in a multivariable system of interconnected tanks using as a prototype a simulated model of instrumented plant (Recalde and Burbano, 2006) however, the real time application using MatLab did not show a good performance. A similar work using the predictive control in a coupled system of two tanks by MatLab interface was developed, concluding that it allows reducing the costs of investment in hardware but with a high computational cost (Moromenacho, *et al*., 2010). It has also been worked on more complex coupled systems as is the case with the adjustment, configuration and control of four coupled tanks in which a decentralized multivariable control is designed using two PI (Proportional-Integral) controlling the level of two reservoirs by means of the tension of two pumps that feed the tanks under control; a good reference tracking it is achieved and the interactions between loops are reduced (Castelo, *et al.*, 2009).

The system by neural networks is one of the techniques that since the 1990's has taken relevance by the attempt to design intelligent controllers (Ponce, 2010). Its use makes it possible for the dynamic of complex systems to be modeled and precise control is achieved through the training, without having a priori information about the system parameters (Parker, 1995). This is how the level control of a tank through neural networks using the direct control by inverse model and the control Feedforward is made in (Garrido, *et al.*, 2009); it is concluded that in the controller on Feed forward the variable level reaches the reference value, it has fewer oscillations and the settling time is lower than in the direct control. Following similar work, a function was developed with neural networks based on sliding mode for the control of a system of coupled tanks; the results show that the appropriate control of the tanks is achieved, however, it is only done through simulation, it is not implemented (Aliasghary, *et al.*, 2011).

The design of a controller based on neural networks with genetic algorithms and multipurpose optimization is implemented in a prototype system of tanks, showing a good control performance (Vassiljeva, *et al.,* 2014). The control approach based on neural networks to a coupled system of tanks is used in another work; in this system, it is experienced with a hybrid system between neural networks and classical PID control (Ramli, *et al*., 2009).

Currently, at the Surcolombiana University there is a system of coupled tanks on which a fuzzy logic control algorithm based on microcontroller has been previously made (Soto, *et al.,* 2014). In this way, it is intended to continue with the development of new techniques of control over such a system and therefore the contribution of this work is the development of the design and implementation of a controller based on neural networks for the hydraulic system MIMO (Multiple Input Multiple Output) of level and flow. To fulfill this purpose, the interaction between the variables is evaluated and finally the interface is performed in Simulink that complies with the task of monitoring, control and visualization of the system in real time.

2. MATERIALS AND METHODS

2.1 Hydraulic system

In this hydraulic system is required to control the level and output flow of the main tank (T2) shown in the Figure-1. As it can be seen the system is also composed of a reserve tank (T3) responsible for supplying the liquid to

T2, a tank of disturbance (T1). Additional to this, there are the level sensors (S1) and flow (S2), the actuators, the submersible pump (B1) and the electrovalve of control (V2). Finally, the electrovalve of disturbance (V1) is presented.

2.2 Data acquisition

On this first stage, it is necessary to collect the data that correctly describe the real behavior of the system, because this depends on the successful development of the following stages and consequently an optimal control for the system.

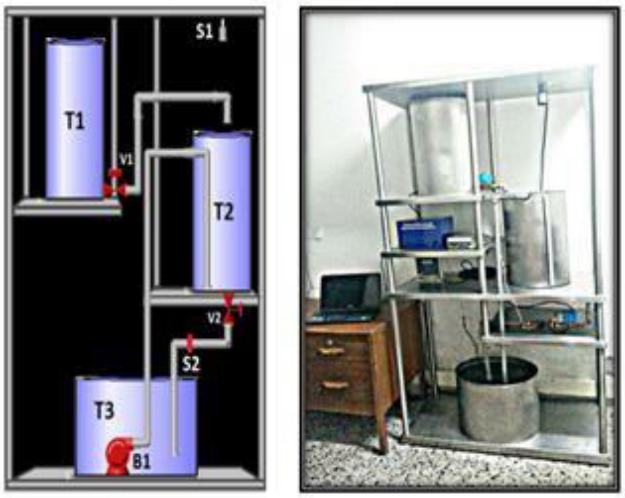

Figure-1. Hydraulic System. a) Simulated. b) Real.

To make the acquisition of data a Simulink file has been created (Figure-2), in which the serial communication between the Arduino Mega development card and the computer is incorporated; besides the necessary calculations are carried out to convert the voltage signals of level to centimeters and flow to L/min. It is decided to use the Pulse Width Modulation (PWM) to provide the control voltages to the actuators, because they improve the performance of the system by controlling the amount of power delivered to the load without considerable loss of power or heating of the devices. In addition, it allows a maximum variation of the duty cycle from 0% to 100%.

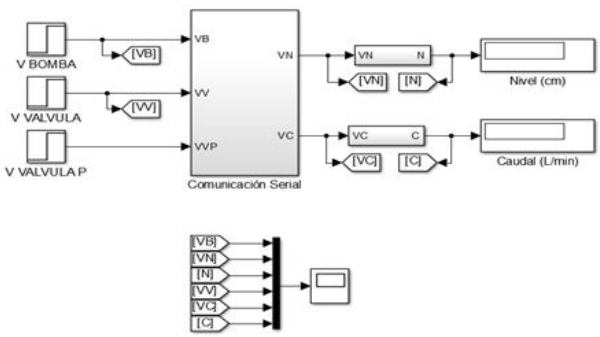

Figure-2. Data acquisition with Simulink.

The voltage applied to the submersible pump B1 (VB) and the voltage applied to the electrovalve V2 (VV) is considered as process inputs. The voltage delivered by the level sensor (VN) and the voltage delivered by the flow sensor (VC) are considered as the outputs of the process. The level delivered by the level sensor is referred to as N and the flow delivered by the flow sensor as C.

2.3 Evaluation of the interaction between variables

Due to the system is multivariable, as it can be seen in Figure-3, and according to the literature review, it is decided to apply the Bristol method (Smith, Corripio, 1997) to evaluate the interaction between the input and output variables of the process.

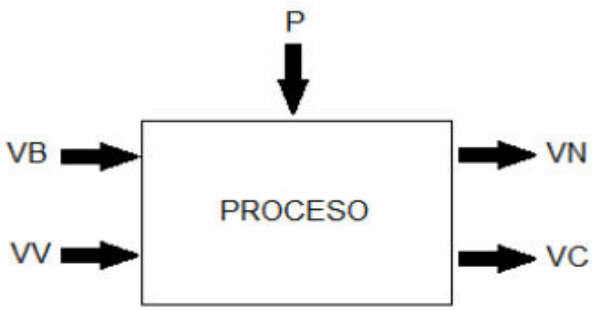

Figure-3. Process variables.

To determine the interaction, two experimental tests are performed that involve on applying a constant step during the entire time of the test to an input variable, while the other variable is subjected to a step change in the time to and thus observing the response of the output variables (Figures 4 and 5).

Figure-4 shows that change in the step of VB increases the slope of VN, but no variation in VC is evidenced. In Figure-5, the change in the step of VV generates a variation in VC. Also an insignificant variation in the slope of VN is noted.

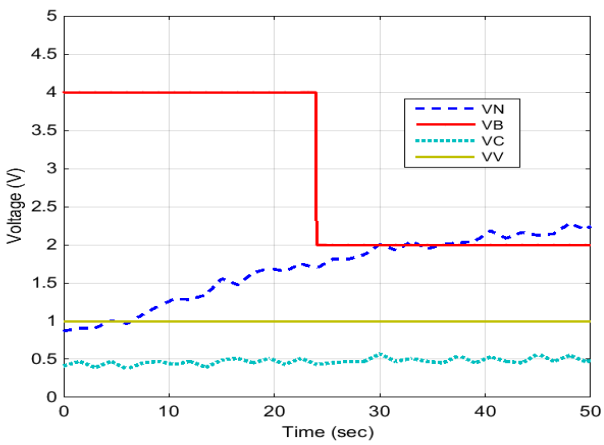

Figure-4. Test 1: Response process to a step change in VB.

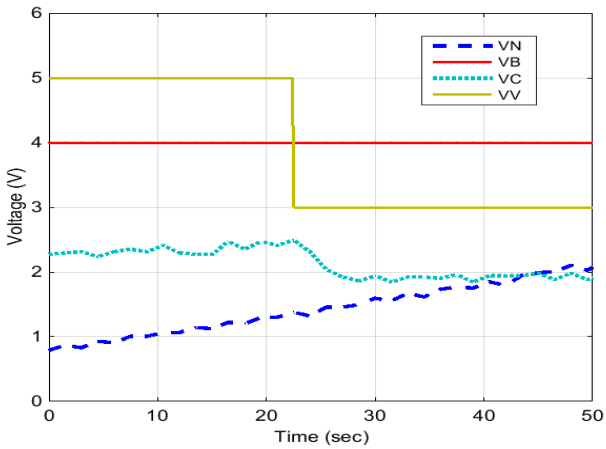

Figure-5. Test 2: Response process to a step change in VV.

Once this information is obtained, the open loop gains are calculated and the relative gains for each variable and the array of relative gains are obtained (Smith, Corripio, 1997). The gains in open loop for 2x2 systems are the following.

$$K_{11} = \left.\frac{\Delta c1}{\Delta m1}\right|_{m2} \qquad K_{12} = \left.\frac{\Delta c1}{\Delta m2}\right|_{m1}$$

$$K_{21} = \left.\frac{\Delta c2}{\Delta m1}\right|_{m2} \qquad K_{22} = \left.\frac{\Delta c2}{\Delta m2}\right|_{m1}$$

Where K_{ij} is the relative gain that relates the controlled variables (ci) with the manipulated variables (m_{ij}), making a change in each manipulated variable while the others remain constant. The relative gains can also be calculated based on the open loop gains according to the following equations:

$$\mu_{11} = \frac{K_{11}K_{22}}{K_{11}K_{22} - K_{12}K_{21}} \qquad \mu_{12} = \frac{-K_{12}K_{21}}{K_{11}K_{22} - K_{12}K_{21}}$$

$$\mu_{21} = \frac{-K_{12}K_{21}}{K_{11}K_{22} - K_{12}K_{21}} \qquad \mu_{22} = \frac{K_{11}K_{22}}{K_{11}K_{22} - K_{12}K_{21}}$$

The result is shown in Table-1 where is evidenced that the system can be treated as two uncoupled SISO subsystems and it is established that the level must be controlled by VB and the flow by VV as it is shown in Figure-6, given the high degree of interaction that occurs between the input and output variables mentioned.

Table-1. Matrix of relative gains.

		Manipulated Variables	
		VB	VV
Controlled Variables	Level	1	0
	Flow	0	1

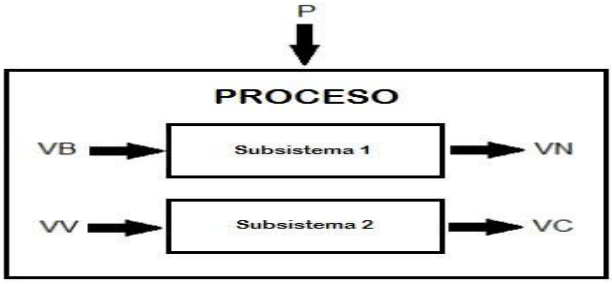

Figure-6. Process diagram uncoupled.

2.4 Controller design for the level variable

It takes as a manipulated variable the voltage applied to the pump (VB) and as controlled variable the level voltage (VN). A control by internal model is applied, considering that the inputs of the network are the real output of the plant and the error between the output of the direct model and the actual output of the plant.

With the Neural Network Toolbox of MatLab, the algorithm responsible for creating the neural network developed using the data of the voltage level error and the level voltage level (VN), which has a hidden layer with 13 neurons and an output layer with 1 neuron. For the selection of the number of neurons in the hidden layers, there is no rule, tests must be applied and choose the number which has the best performance (Rocha, Escorcia, 2010). The activation function used for the hidden layer was hyperbolic tangent sigmoidal, which being a non-linear function allows the network to learn linear and non-linear relationships between the input and the output. The activation function used for the output layer is linear because it does not modify the calculated output by the hidden layer and in addition, it can take any value (Llano; *et al,* 2007). The training method selected was the Levenberg-Marquardt, considering that is specifically designed to reduce the mean squared error (MSE); a fundamental parameter in the design of neural controllers (Zarza; Tribaldos, 2012), (Goméz; *et al,* 2013).

In Figure-7 it can be seen that the training is successful. The mean squared error (MSE) indicates the distance between the estimation of the test values of the model and the values of the real test, so the closer to zero is this value, the better it will be; in this case, the MSE was 9.972e-08 which was achieved in 105 epochs.

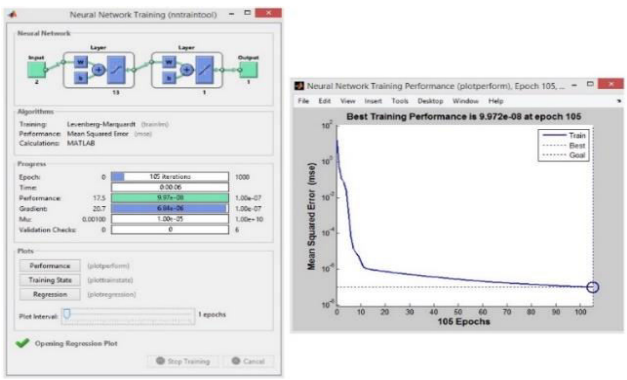

Figure-7. Neural network training of level.

2.5 Controller design for the flow variable

In the design of the controller for the second subsystem the voltage applied to the control valve VV is taken as a manipulated variable and the flow voltage VC as a controlled variable. By using the Neural Network Toolbox of MatLab is developed the algorithm in which the neural network of the inverse model of the system is created, formed by a hidden layer with 5 neurons and the output layer with 1 neuron. The activation functions used are the same of the neural network for the control of the subsystem 1, in the hidden layer the hyperbolic tangent sigmoidal function and in the output layer the linear function. The method used for training is also Levenberg-Marquardt's. In Figure-8, is noted that the MSE is 8.2241e-08 so that it can be stated that the training was successful.

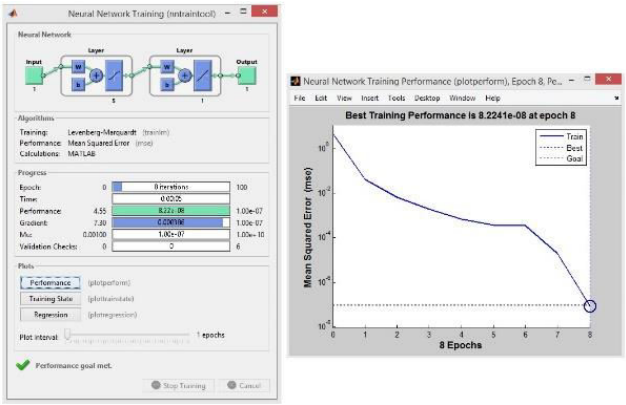

Figure-8. Neural network training of flow.

The real time control interface developed in Simulink, through which the controller tests are carried out it is shown in Figure-9.

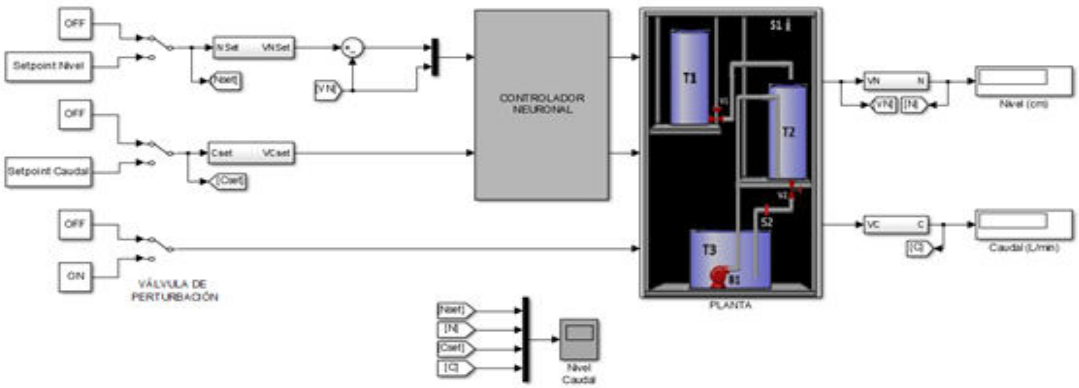

Figure-9. Control system based on neural networks in real time.

3. RESULTS AND DISCUSSIONS

The results of the real time control tests are shown from Figures 10 to 16. In Figure-10 the response of the controlled level for changes in its setpoint is shown.

Figure-12 shows the controlled flow response for different changes in its setpoint. In this test it is observed that the flow is established approximately 5 seconds after the change has occurred; except in the first time interval where the flow fails to reach the setpoint in 5 seconds as would be expected, due to the bubbles that appeared in the pipeline, which turns turbulent fluid and only until 17 seconds reaches a laminar flow.

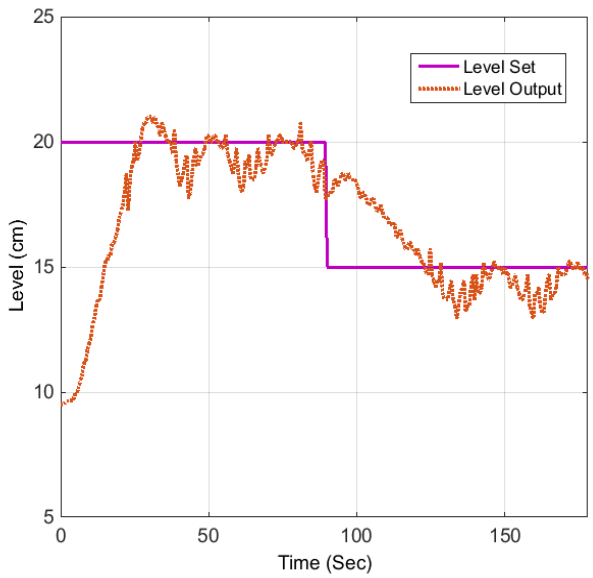

Figure-10. Controller response for changes in set level.

Some fluctuations in the variable level due to the disturbance caused by the output flow are also shown considering an initial level of liquid in T2 of 10 cm.

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In Figure-11 the settling time of 5 seconds for the flow it is observed, by applying a constant flow of liquid output of 5 L/min.

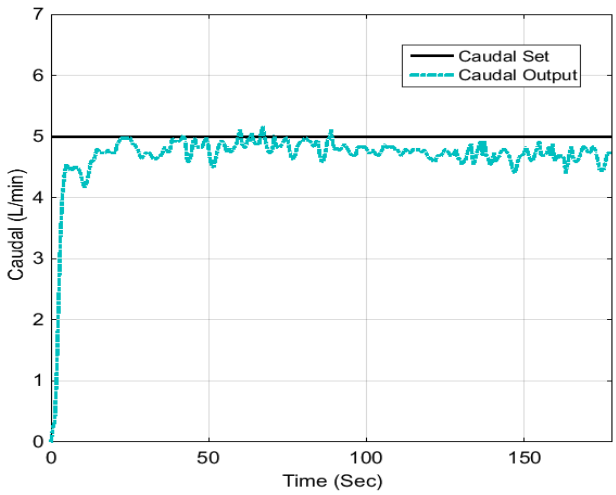

Figure-11. Controller response for constant output flow in 5 L/m.

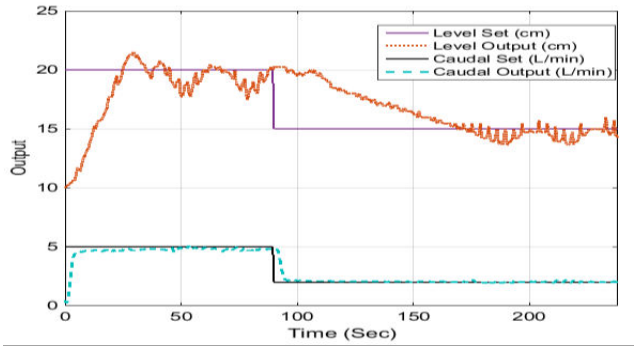

Figure-12. Controller response for changes in setpoint flow.

In Figure-13 the response of the level is shown by applying a constant liquid level of 30 cm.

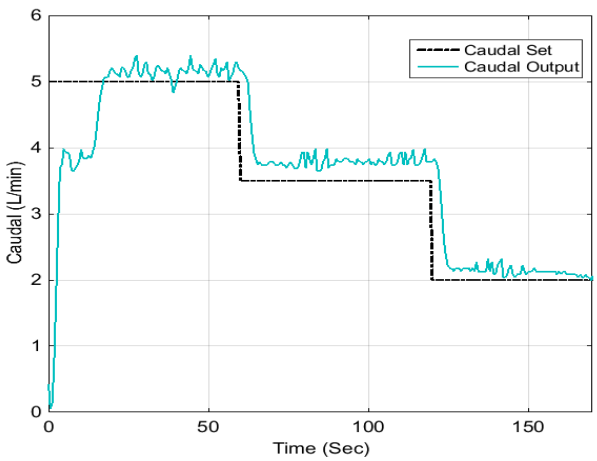

Figure-13. Controller response for constant output level in 30 cm.

In Figure-14 changes are applied to both the level and flow setpoint. It is observed in this test that in the time interval from 90 to 240 seconds at the level it takes a longer time to reach its next setpoint because it changes from a higher value to a lower one and that the output flow of liquid is not the maximum.

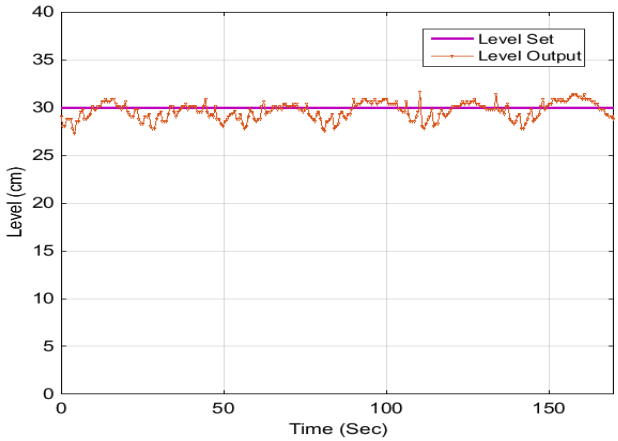

Figure-14. Controller response to different changes in setpoint level and flow.

Figures 15 and 16 show the robustness of the designed controller to a disturbance applied to the level in 100 seconds. It is observed the recovery of the level signal by action of the level controller (Figure-15) and the response of the flow that remains unchanged when the disturbance is applied (Figure-16).

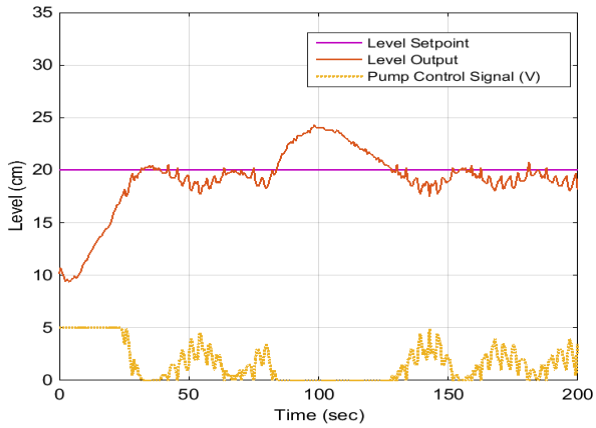

Figure-15. Response to the level controller subjected to a disturbance at 100 sec.

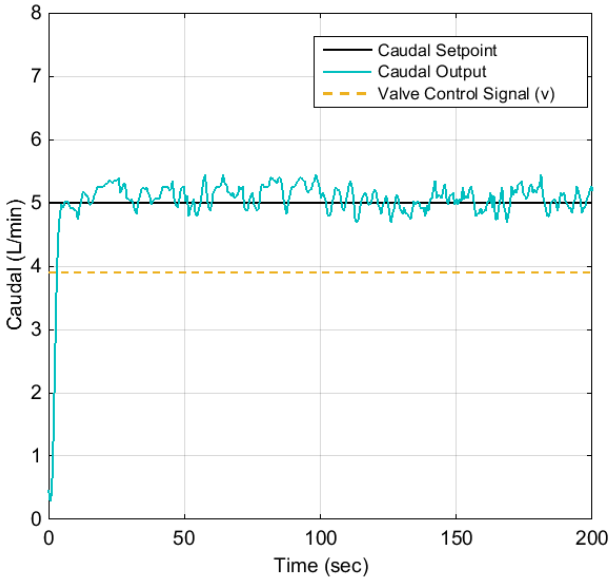

Figure-16. Response to the flow controller to the disturbance in the level.

By comparing the results of all the tests carried out, it can be observed that the variable flow is established at approximately 5 seconds, except when there are air bubbles in the pipe, which turns turbulent the fluid and only sets when a laminar flow is achieved. The settling time of the variable level depends on the setpoint value that is wanted to achieve besides the flow that is coming out at that moment, because this represents a disturbance to the level control, which causes fluctuations in the steady state response of such a variable.

Based on the tests carried out, the control performance is evaluated taking into account three parameters: the overshoot, the steady state error and the settling time.

The overshoot is the maximum peak value obtained from the response curve, measured from the desired value. In this control does not exist any overshoot for none of the two controlled variables, in the level some variations are shown which are not considered overshoot because they are caused by the disturbance that occurs when there is an output flow.

The steady state error is the difference between the desired value and the stationary state value of the response curve, this latter is obtained by calculating the linear regression of the curve from the moment in which it stabilizes. For the implemented control, is noted that the percentage of error is very small, being the maximum value of the tests performed 0.01%.

The settling time is defined as the minimum time in which the response curve reaches and maintains a pre-established range. In this control, the settling time for the variable level varies according to the initial value, and the setpoint that is desired to be achieved. For the variable flow, the settling time remains almost the same no matter the initial conditions and its setpoint.

4. CONCLUSIONS

According to the array of gains obtained by applying the Bristol method, there is no interaction between the VB-VN and VV-VC loops, so the hydraulic system can be considered as two independent SISO systems. Therefore, the use of decoupling techniques are not necessary.

The inverse model technique allows the development of neural controllers with particular characteristics according to the type of application required. In the case of the flow variable, by showing a dynamic of moderate complexity, the technique of simple inverse model is enough to establish a direct relationship between the input and the output, without requiring a feedback or a processing of the current state of the controlled variable.

When the behavior of the variable to be controlled is more complex and is also exposed to disturbances, as in the case of the level, it is necessary to use a variation of the inverse model known as internal model, which allows to examine the current conditions of the controlled variable, evaluating the error and take the necessary corrective actions to achieve the desired setpoint.

As a disadvantage of the implemented control, the computational cost is mentioned which can be increased since the acquisition and control are both done through the MatLab interface. Although on the tests it is shown that the work in real time presents a delay that doesn't significantly affect the response of the system, the option of working with tools of better performance in real time as LabVIEW or free software is proposed.

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