

Recurrent Fuzzy Wavelet Neural Network to Control a PCV

Mohammad Heidari*

Mechanical Engineering Group, Aligudarz Branch, Islamic Azad University, P.O. Box 115, Aligudarz, Iran;
moh104337@yahoo.com

Abstract

Pneumatic Control Valves (PCV) are used in the process industries. In this paper, a Recurrent Fuzzy Wavelet Neural Network (RFWNN) is constructed by using Recurrent Wavelet Neural Network (RWNN). In RWNN, temporal relations are embedded in the network by adding feedback connections on the first layer of the network, and wavelet basis n is used as fuzzy membership function. The proposed method is applied on a PCV. P, PI and PID controllers are also employed for comparison. Bondgraph method has been utilized to model the control valve, so as to compare the response characteristics of valve. Simulation results have been made for four controllers.

Keywords: Control Valve, Bondgraph, Recurrent Fuzzy Neural Network

1. Introduction

Process industries involve control loops all networked together to develop a product to be offered for sale. The design of each control loop is of great importance. It should be in a way that guarantees the quality of the end product through keeping such important variables as pressure, flow, level, temperature, etc. within required operating range. Some disturbances may be received and internally caused by any of these loops so that they can have a detrimental effect on the process variable; Moreover, the interaction of other loops in the network leads to the same result. To reduce the effect of disturbances, sensors gather information about the variable and its relationship to some desired set point. The data is processed by a controller to determine what must be done to get the process variable back to where it should be after the occurrence of a disturbance. A method is chosen by the controller to be implemented by a type of final control element after all the measuring, comparing, and calculating are done.

Control valve is regarded as the most common final element in the process control industries. This way, the load disturbance is compensated and the regulated process

variable are kept to the nearest desired set point. Figure 1 shows an actuator of sliding-stem control valve.

Now PC valves are used in many industries. So the design of CV to be a very challenging task. Valve body housing and the actuation unit are two main components of the control valves. Champagne et al.¹ reviewed the pneumatic actuator of CV and positioner parameters that affect the control performance. This is done using a control valve package computer model to assess the dynamic performance. The effects of supply pressure, step size, load margin, and flow, actuator volume and design style are studied using mathematical simulations of PCV dynamic performance. Hagglund² introduced a procedure so as to compensate for static friction in PC valves through adding pulses to the control signal. The characteristics of the pulses are determined from the control action. The static friction in PC valves causes vibration consequently resulting in losses in quality and expense of new materials. De Souza et al.³ presented a well-known stiction compensation method in order to reduce variability both at process variable and pneumatic valve stem movement. Bondgraph is a graphical representation of a physical dynamics system.

In other words, bondgraphs are multi domain and domain neutral. Moreover, a bondgraph can incorporate

*Author for correspondence

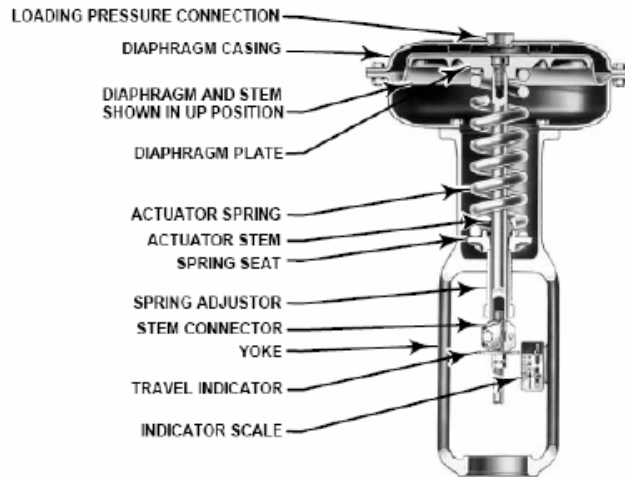


Figure 1. Actuator of the valve.

multiple domains simultaneously. Paynter⁴ devised bondgraphs and subsequently developed into a methodology together with Karnopp and Rosenberg⁵. Thoma⁶, Dixhoorn, and Dransfield are regarded as the early prominent promoters of bondgraph modeling technique among others. To find the proactive fault in 4/3 way direction control valve, the bondgraph method was utilized by Athanasatos and Costopoulos⁷. By comparing the response of the bondgraph model to the response of an actual hydraulic system, its accuracy was verified. Zuccarini et al.⁸ utilized the bondgraph for modeling of an mitral valve.

A application in cardiovascular modeling was demonstrated by focusing on a specific example; a 3D model of the mitral valve coupled to a lumped parameter model of the left ventricle. Heidari and Homaei⁹ introduced a regulator for control valves using pole-placement strategy, optimal control, full-order state observer, and minimum-order state observer.

After comparing their responses it was revealed that minimum overshoot and settling time was obtained using optimal regulator of PCV.

Heidari and Homaei¹⁰ presented a neural planin order to control an actuator of pneumatic control valve.

To identify and control dynamic systems many studies have been carried out on using neural networks¹¹⁻¹³.

Recurrent neural network¹⁴⁻¹⁷ can model the dynamical response of a system. It is a dynamic mapping and represents good performance in the presence of such uncertainties as parameter variations, external disturbance, unmodeled and nonlinear dynamics. Recurrent fuzzy neural network^{18,19} is a modified type of recurrent

neural network, which uses recurrent neural network for realizing fuzzy inference. It is possible to train RFNN using the linguistic experience of human operators, and interpret the knowledge acquired from training data in linguistic for and it is very easy to initialize the structure and parameters of RFNN from linguistic rules. Moreover, with its own internal feedback connections, RFNN can temporarily store dynamic information and deal with temporal problems efficiently.

This research is organized as follows: Section 2 recalls the bondgraph model of the valve and proposes equations of motion of valve. Section 3 presents the RFWNN. Standard PID control method is presented in Section 4. Section 5 shows the results of P, PI, PID and RFWNN controllers for the valve and finally some conclusions are given in section 6.

2. Bondgraph Model of Valve and Equations

Figure 2 shows the bondgraph model of the valve. SE is the input pressure of the valve. The pressure changes to force by multiplying in effect area of the diaphragm. The T.F. shows this transformer in the Bondgraph model of the valve. Friction of the valve is R.

Element *I* is the movable mass of valve and diaphragm. Element *C* represents the spring of the valve actuator.

Also 1-junction is a common flow junction. 1-junctions have equality of flows and the efforts sum up to zero with the same power orientation.

In fact, junctions can connect two or more bonds. The direction of the half arrows ($\rightarrow$) denotes the direction of power flow given by the product of the effort and flow variables associated with the power bond. The two 1-junctions in the bondgraph shown can be uniquely determined as (S 1 2) and (S 4 5 6); similarly symbols like SE_1 , R_6 can be used to identify a particular element. P_4 and q_5 are two

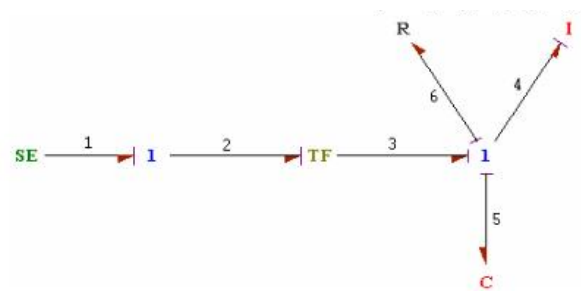


Figure 2. Model of the Bondgraph⁹.

state variable of this model. q_5 is the displacement of valve stem and the variation of the spring length. Also $v_4 = \frac{P_4}{I_4}$ is the velocity of the valve stem. The equations of motion using bondgraph method are as follows:

$$\dot{P}_4 = A \times SE_1 - K_3 q_5 - \frac{R_6}{I_4} P_4 \quad (1)$$

$$\dot{q}_5 = \frac{P_4}{I_4} \quad (2)$$

If the velocity and position of the valve stem were zero in the initial condition so:

$$X(0) = \begin{bmatrix} P_4(0) \\ q_5(0) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

The transfer function of the valve is obtained by derivation of equation (2) with respect to time:

$$\ddot{q}_5 = \frac{\dot{P}_4}{I_4} \quad (3)$$

With substitution of $\dot{P}_4$ from equation (1) in to equation (3):

$$\ddot{q}_5 = \frac{A \times SE_1 - K_3 q_5 - \frac{R_6}{I_4} P_4}{I_4} \quad (4)$$

By substitution of P_4 from equation (2) in to equation (4):

$$\ddot{q}_5 = \frac{1}{I_4} (A \times SE_1 - K_3 q_5 - R_6 \dot{q}_5) \quad (5)$$

By applying the laplace transform to equation (5):

$$\frac{q_5(s)}{SE_1(s)} = \frac{(A/I_4)}{s^2 + (\frac{R_6}{I_4})s + (\frac{K_3}{I_4})} \quad (6)$$

Equation (6) is the transfer function of the valve. The results of bondgraph model of valve show that the response of the system is identical with the result in^{9,10,21}.

3. Construction of RFWNN

Figure 3 shows the topology of the RFWNN, which comprises n input variables, m term nodes for each input variable, l rule nodes, and p output nodes. Using u_k^i and O_i^k to denote the input and output of the i th node in the k th layer separately, the signal propagation and the operation functions of the nodes in each layer are introduced

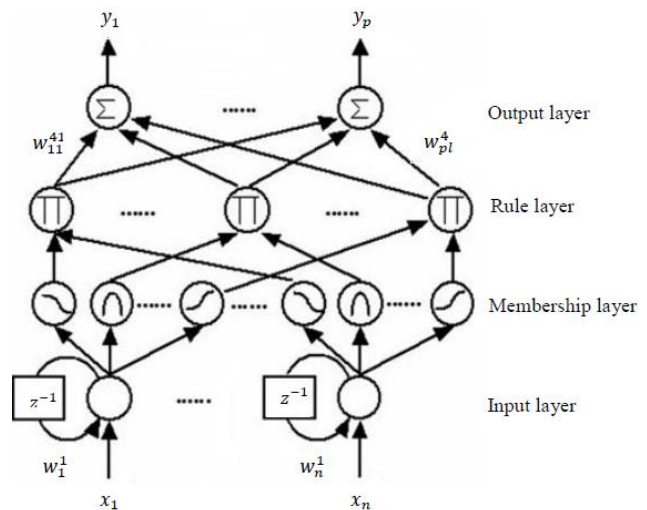


Figure 3. Topology of RFWNN.

as follows. Input layer accepts input variables. Its nodes transmit input values to the next layer. Feedback connections are added in this layer to embed temporal relations in the network.

$$u_i^1(k) = x_i^1(k) + w_i^1 O_i^1(k-1), \quad (7)$$

$$O_i^1(k) = u_i^1(k)$$

In equation (7), $i=1,2,\dots,n$; k is the number of iterations and w_i^1 is the recurrent weights.

Each node performs a wavelet basis function.

$$u_{ij}^2 = \frac{O_i^1 - a_{ij}}{b_{ij}}, \quad O_{ij}^2 = h(u_{ij}^2) \quad (8)$$

where $i=1,2,\dots,n$ and $j=1,2,\dots,m$.

$h(\cdot)$ is a mother wavelet used in this paper, which is defined as follows:

$$h(x) = \cos(0.25x) \exp(-x^2)$$

a_{ij} and b_{ij} in (8) are the dilation and translation parameters of the wavelet function, the subscript ij indicates the j th term of the i th input variable. Rule layer forms the fuzzy rule base and realizes the fuzzy inference. Each node is corresponding to a fuzzy rule. Links before each node represent the preconditions of the corresponding rule, and the node output represents the firing strength of corresponding rule. The q th node of layer 3 performs the AND operation in q th rule. It multiplies the input signals and output the product. Using $O_{iq_i}^2$, $q_i \in \{1, 2, \dots, m\}$, to denote the membership of x_i to its corresponding linguistic term in q th rule, then the input and output of q th node can be defined as:

$$u_q^2 = \prod_{i=1}^n O_{i_{qi}}^2, O_q^3 = u_q^3, q = 1, 2, \dots, l. \quad (9)$$

The input and output of *sth* node can be calculated as follows:

$$u_s^4 = \sum_{q=1}^l w_{sq}^4 O_q^3, O_s^4 = \frac{u_s^4}{\sum_{q=1}^l O_q^3} \quad (10)$$

Where $s = 1, 2, \dots, p$ and w_{sq}^4 is the weight, which indicates the output action strength of the *sth* output associated with the *qth* rule. So it is evident that the proposed RFWNN is a fuzzy logic model with memory elements in the first layer.

4. PID Controller

The PID control can be defined as:

$$u(t) = K_p e(t) + \frac{K_p}{T_i} \int_0^t e(t) dt + K_p T_d \frac{de(t)}{dt} \quad (11)$$

In equation (10), $u(t)$ and $e(t)$ are the controller output and error signal. In equation (10), T_i and T_d are the integral time and derivative time constants respectively. The Laplace transform from equation (11) is:

$$U(s) = K_p E(s) + \frac{K_p}{T_i s} E(s) + s K_p T_d E(s) \quad (12)$$

So the PID controller transfer function is:

$$\frac{U(s)}{E(s)} = K_p \left(1 + \frac{1}{T_i s} + T_d s \right) \quad (13)$$

K_p is the proportional gain. K_i the integral gain and K_d the derivative gain can be defined as follows:

$$K_I = \frac{K_p}{T_i}, K_D = K_p T_d \quad (14)$$

A performance index can be calculated and used to assess the performance of the valve model. A system is regarded as an optimum control system when the system parameters are adjusted so that the index reaches an extreme, commonly a minimum value.

To decrease the part of the large initial error to the value of the performance integral, as well as to emphasize errors occurring later in the response, the following index has been proposed²⁰.

$$ITAE = \int_0^\infty t |e(t)| dt \quad (15)$$

In equation (15), t , is time and $e(t)$ is absolute error. The ITAE criterion, is the one that minimizes the performance index that has been given in equation (15). A system designed by use of the ITAE criterion has a characteristic that the overshoot (OS) in the transient response is small and oscillations are well damped.

5. Results and Discussion

Table 1 shows the parameters for a sample sliding-stem PCV. By substitution of Table 1 parameters in equation (6), we have:

$$\frac{q_5(s)}{SE_1(s)} = \frac{6.53}{s^2 + 33.33s + 226333.3}$$

The performance of the control strategy is proposed in this part through a series of simulations. The PID control is perhaps the most widely used control method. It can provide fast response, good system stability and small steady state errors in linear system with known parameters. The simulation results are presented below. They demonstrate the effects of different controllers on the performance of the control system. We want to design the P, PI and PID controllers such that in the Unit Step Response (USR) the maximum overshoot is less than 10% and settling time is equal to 0.5 sec.

Figure 4 shows results of the USR of valve without any controller. In this case, the OS is very high and the settling time is also 0.178 second. The output has an OS less than 90% and rise time (RT) is 0.00337 seconds. Using the P controller for valve system, the results of the OS and settling time for closed loop system is shown in Figure 5. The best gain parameter is 1.012. The OS is very big and it is 89.6%. Also the settling and RT are 0.178 and 0.00337 second respectively. So the P controller is not suitable for this problem. Figure 6 shows the results for the PI controller. The gain parameters of the PI controllers were chosen

Table 1. Valve parameters²¹

Name of Variable	Parameter	Value
Effective area of diaphragm	A	0.196 ft ²
Spring constant	K	6790
Movable mass	I (M)	0.03 slug
Resistance and friction coefficient	R	1lb.S/ft
Air pressure	SE	140 lb/ ft ²

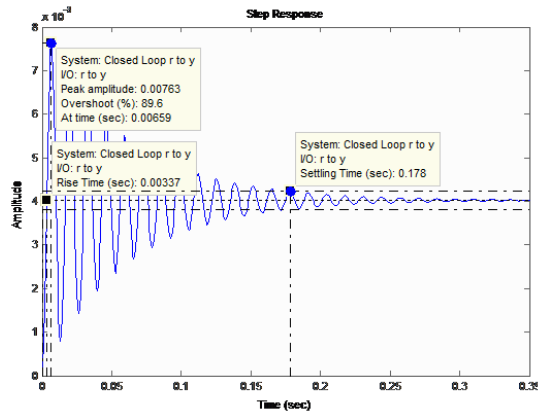


Figure 4. The USR of valve without any controller.

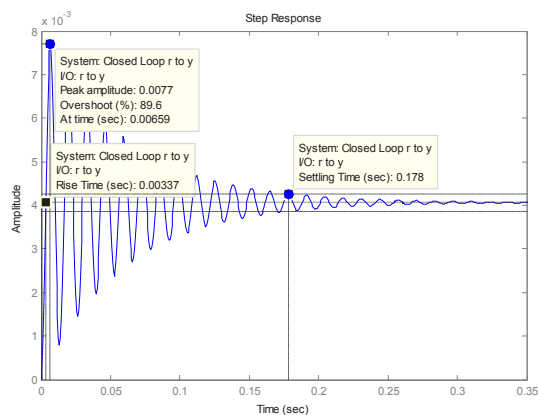


Figure 5. The USR of valve (P controller).

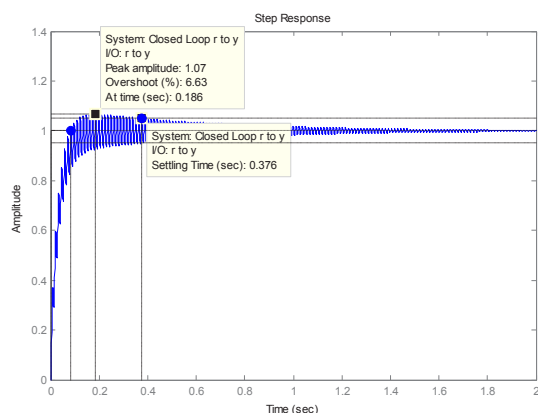


Figure 6. The USR of valve (PI controller).

with singular frequency method and the gains are set to $K_p = 20$, $K_I = 8000$.

Singular frequency method implements robust control design strategy to locate stabilizing PID regions in parameter space²².

From Figure 6, OS and settling time are 6.63% and 0.376 second and the RT is 0.0831 sec.

Figure 7 shows the PID controller results for OS and settling time. The tuning algorithm is singular frequency²² and performance metric was Integral Time Absolute Error (ITAE). The gain parameters of the PID such as, K_p , K_I and K_D obtained and set to $K_p = 7570$, $K_I = 1.514e - 4$ and $K_D = 15.21$. From the figure 7, the settling time is 0.22 second and OS is very small. The output has an OS less than 5%. The RT is 0.0967 sec.

Figure 8, shows the USR of PCV with RFWNN. In this case, the OS is very small and the settling time is also 0.209 second. The output has an OS less than 0.55% and RT is 0.226 seconds.

Table 2 shows the results of four controllers for the penumatic control valve.

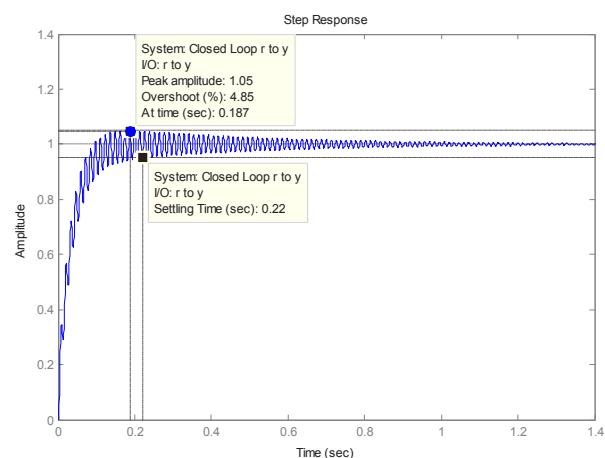


Figure 7. The USR of valve (PID controller).

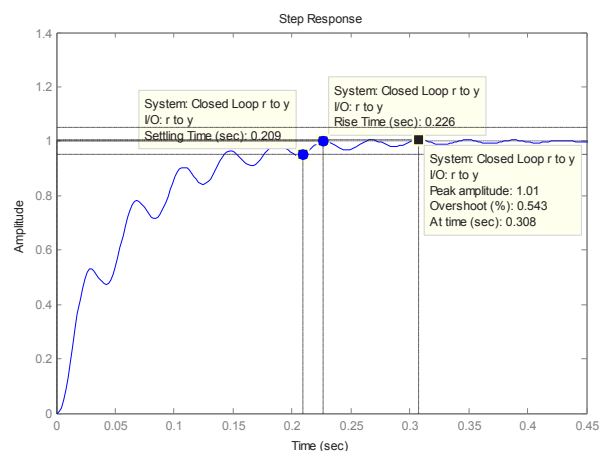


Figure 8. The USR of valve (RFWNN controller).

Table 2. Results of controllers for valve

Controller	Overshoot (%)	Settling time (sec)	RT (sec)
P	89.6	0.178	0.00337
PI	6.63	0.376	0.0831
PID	4.85	0.22	0.0967
RFWNN	0.543	0.209	0.226

6. Conclusion

In this research an RFWNN is used for control of PCV. The RFWNN consists of layers and the feedback connections are added in first layer. Wavelet mother is used as fuzzy membership. This RFWNN can be used for control of the valve. For identification, RFWNN only needs the current inputs and most recent outputs of plant as its inputs. Finally, in this paper, the proposed control scheme based on RFWNN is used to control the pneumatic control valve system and simulation results verified its effectiveness.

7. References

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