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Dynamic Modeling of Liquid-Flow Process due to Hysteresis of Pneumatic Control Valve

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Abstract- **The study of pneumatic control valve with hysteresis phenomena has significant importance in process control industries. It is caused by the friction between the stem and packing. It is a nonlinear phenomenon and cannot be expressed by a transfer function. In the present study, a liquid-flow process is considered with an equal percentage pneumatic control valve as a final control element. The control valve has excessive hysteresis. Valve hysteresis strongly influences the dynamic behaviour of a liquid-flow process. Due to hysteresis the model of the open loop flow process is constructed in upward and downward motion of valve stem using neural network with backpropagation technique and general polynomial function. NATIONAL INSTRUMENTS™ based hardware and software tools (LabVIEW™) and MATLAB® R2008a are used for precise and accurate acquisition, flow measurement, control action and simulation. The closed-loop control of a liquid-flow process is simulated with the constructed model. The effectiveness of the simulated model is verified by comparing the simulation results with the real time results in closed loop. It is observed that simulation results are very close to the real time ones.**

Index Terms— **Hysteresis, pneumatic control valve, Liquid-Flow Process, PID**.

1. INTRODUCTION

In process control, the most serious form of hysteresis is encountered in pneumatic control valves. The control valve is the weakest link in the control system because it is the only moving part and due to the presence of friction it is subjected to varying dynamics quite often. The major causes of control valve problems are nonlinearities such as hysteresis, stiction, backlash, and deadband. Due to these, the pneumatic control valve's stem movement does not follow the control signal accurately but deviates from it. In other words, the relationship between controller output and controlled variable often changes. All valves have some hysteresis, but excessive valve hysteresis typically occurs when the valve sticks as it tries to open and close. This can happen for a number of reasons including overtightened packing. Therefore, hysteresis is the one of the biggest problems associated with the final control element. This can be roughly defined as the maximum difference obtained in stem positions for the same input up-scale and down-scale [1, 2].

A final control element is one of the basic components of any control system, which comes in a variety of forms depending on the specific control application. Its common type in chemical process industry is the pneumatic control valve, which regulates the flow of fluids [3]. They are activated by air pressure signals. Their valve stems are moved up or down, causing more, or less valve opening. If increasing the air pressure signal causes the valve opening to increase, the valve action is said to be "air-to-open" and if increasing the air pressure signal causes a reduction in valve opening, the valve action is said to be "air-to-close" [4].

Types of control valves are classified by a relationship between the valve stem position and the flow rate through them. There are three most common control valve flow characteristics. For a valve with *linear flow characteristic*, the flow is directly proportional to the percentage of valve opening. For the *quick opening flow characteristics*, larger flow is obtained at the lower valve opening positions. In the *equal-percentage flow characteristic*, equal increments of valve travel produce equal percentage changes in the existing flow [4, 5, 6, 7, 8].

In process industries, pneumatic control valves are the most commonly used actuators or final control elements. But in practice it is very difficult to do the modeling of any plant or process having a final control element with hysteresis. Hysteresis is a nonlinear phenomenon and cannot be expressed by a transfer function. Therefore simulation of such a plant or process is not an easy job. So far very little work has been reported in the literature regarding the effective modeling of a plant or process having hysteresis elements. Choudhary *et al*. gives the definition of stiction in terms of valve nonlinearity, such as hysteresis, and propose an empirical data driven model of valve stiction based upon input signal and the specification of deadband plus stickband and slipjump [10-13]. Jelali proposes a technique for the detection and estimation of valve stiction in control loops using least square and global search algorithms [14]. The purpose of this work is to develop a model based upon the input output data using a neural network and general polynomial function.

The present work is focused on the dynamic modeling of hysteresis of a liquid-flow process in the Process Control Unit available in the Advanced Process Control Lab, NSIT. Normal water is taken as the liquid in the present work. NATIONAL INSTRUMENTS™ (NI) based hardware and software tools (labVIEW™) and MathWorks™ (MATLAB® R200a & Neural Network Toolbox™) are used for exact and perfect acquisition, measurement, control and simulation. The liquid-flow process is controlled by manipulating a pneumatic control valve, having the equal percentage characteristic. Due to it equal percentage characteristics it shows nonlinear behaviour. Also, the control valve has excessive hysteresis characteristic. The modeling of the open loop liquid-flow process is done along the upward and downward travel of the valve stem with a general polynomial function and

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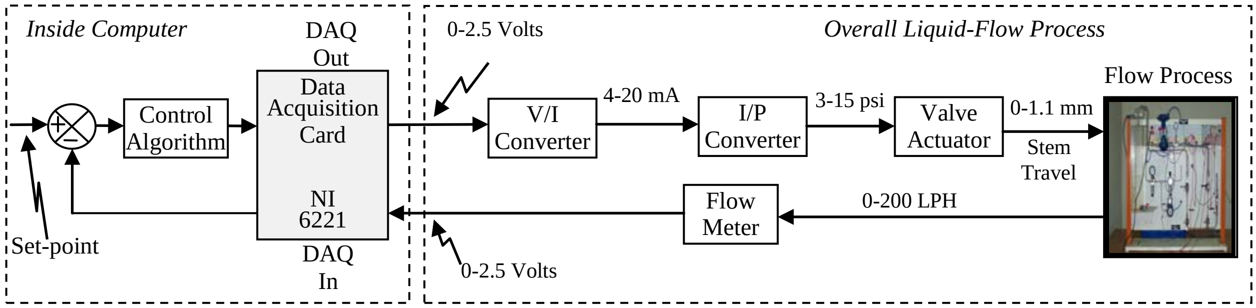

Fig. 1. Block diagram of closed loop control of a liquid-flow process

neural network. The closed loop control of the flow process is successfully simulated with the constructed model. The simulated results match with the real time closed-loop control results.

2. Experimental Setup

2.1 Closed-Loop Control

The block diagram of closed loop control of a liquid-flow process is shown in Fig. 1. The process reflects the typical prototype of a part of plants as in food, soft drink and petroleum industry. The flow-rate is measured using a turbine type flow-meter. It is converted into current signal (4 – 20 mA), which is then converted into voltage signal (0 – 2.5 volts) and this output signal of the plant is sent to the desktop computer through the Data Acquisition (DAQ) card. The input voltage signal (0 – 2.5 volts) to control the opening of the control valve is fed to V to I converter (4 – 20 mA) and then to I to P converter (3 – 15 psi) and the resulting pressure is used to control the pneumatic control valve.

2.2 Data Acquisition

A PCI compatible data acquisition (DAQ) card NI-6221 is used to acquire the data and also to generate the control signal. It is a low-cost multifunction M series DAQ card optimized for cost-sensitive applications. It is a plug-and-play card manufactured by the NATIONAL INSTRUMENTS™. It is plugged inside the PCI slot of the Desktop Computer. Signals, input to and output from the card are synchronized appropriately. A virtual instrument is developed to achieve this job. The data is acquired at the rate of 10 samples per sec. Some of the features of the DAQ card are given below.

Analog Inputs	: 16 (250 kS/s, 16 bits)
Analog Outputs	: 02 (833 kS/s, 16 bits)
Digital I/O	: 24 - 1MHz
Counter/Timers	: 2 - 32 bits - 80MHz

#kS/s: kilo samples per second

2.3 Pneumatic Control Valve

A pneumatic control valve of the equal percentage characteristics is used to regulate the liquid flow-rate. The control valve is of ½ inch port size, action-“air-to-close”, 10 square inch diaphragm, stroke length 11 mm. Valve flow coefficient “C_V” = 0.44, and air supply = 20 psi. This control valve is utilized in the flow control loop to control the flow of water through it. The input-output characteristic of the control valve shows highly nonlinear behaviour. The control valve hysteresis curve is shown in Fig. 2. It shows the percentage change in the controller output and its corresponding percentage change in the stem position. From the curve it is clear that for a controller output there are two values of a stem position. One value corresponds to forward motion of the valve stem and other one to its backward motion. Hysteresis, which is caused by the friction between stem and packing, is a nonlinear phenomenon and cannot be expressed by a transfer function. Therefore, due to the pneumatic control valve the overall system becomes highly complex and nonlinear.

2.4 Transducer

Turbine type flowmeter is used in the Process Control Unit to measure flow through a pipeline. It then converts this flow signal into an electrical signal (in the range of 4-20mA). The range of flow rate is 0 to 200 Liter per hour (LPH). It is calibrated with the help of a rotameter.

2.5 Pump

A pump is used with the following specification: 0.062W, 1/12HP, 2800RPM, 1/2 inch outlet, Head 9 meters I/P=230VAC, 50 Hz. It is mounted over

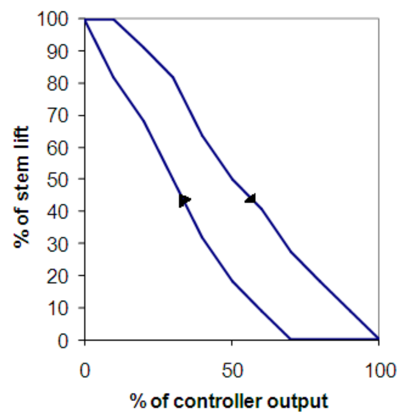

Fig. 2. Pneumatic control valve’s hysteresis

the sump tank top plate. It is piped with a reinforced tube and has a bypass valve as well as one shut off valve to control water delivery even if the shutoff valve is kept off.

2.6 The Input-Output Characteristic of Liquid-Flow Process

The overall liquid-flow process is shown in Fig.1. The control signal is coming through the DAQ card to the process. Its range is from 0 to 2.5 volts. This signal is converted to current signal using V-to-I converter. Further the current signal is converted into pneumatic signal using I-to-P converter. Thus the variation in pneumatic signal across the diaphragm is transferred to the valve stem.

In the present work, the "air-to-close" pneumatic control valve of equal percentage characteristics is used to regulate the liquid flow-rate. As the air pressure signal increases, it causes a reduction in valve opening. The PI controller output in LabVIEW varies between -100 and 100, and is mapped to a value between 2.5 and 0 volts. Therefore, when the control signal is 2.5 volts, air pressure has the maximum value (15 psi); and the valve is in an approximately shut state. When the control signal is 0 volts, air pressure across the valve diaphragm has minimum value (3 psi); and the valve is in a fully open state. Due to the hysteresis behavior of a pneumatic control valve, the characteristic of a liquid flow process depends upon the direction of motion of the valve stem. The input – output characteristic of a liquid-flow process is shown in Fig. 3. As the input voltage signal increases the process follows the path "ABC" and when the voltage signal decreases the process follows the path "CDA". The input and output data of liquid-flow process is given in Table 1.

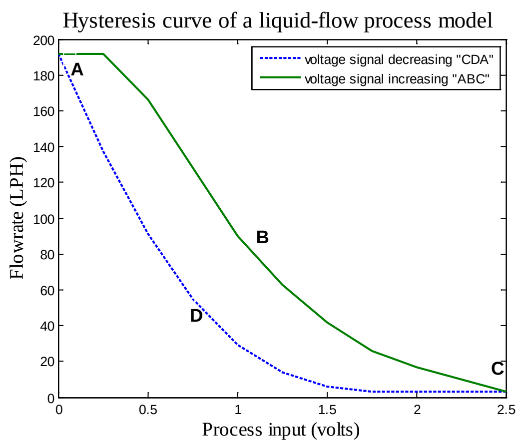

Fig. 3. Input – output characteristic of a liquid flow process

Table 1 Input and output data of the liquid-flow process

Input (volts)	0	0.25	0.5	0.75	1.0	1.25	1.50	1.75	2.0	2.25	2.50
Output Flow-rate (LPH) Path " ABC"	192	192	166	128	90	63	42	26	17	10	3
Output Flow-rate (LPH) Path " CDA"	192	137	91	55	29	14	6	3	3	3	3

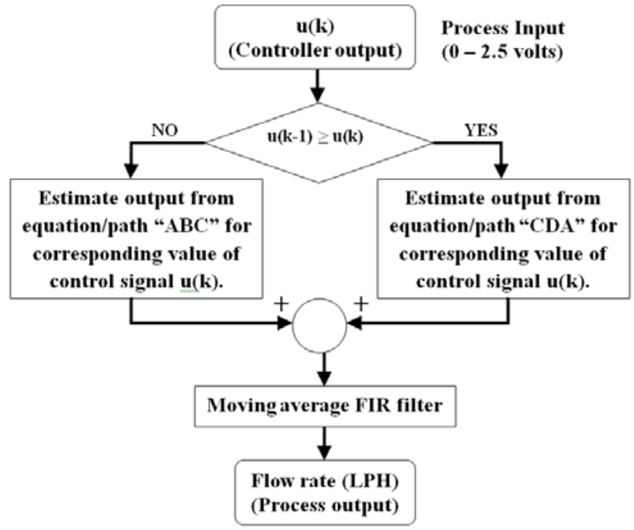

Fig. 4. Signal and logic flow chart of modeling a liquid-flow process

3 Modeling Of Liquid-Flow Process due to Hysteresis of Control Valve

A dynamic process or plant models can be used for simulation studies to get information about the process behavior. It can also be used for control or optimization studies. Process or plant knowledge may be available as physical relationships or in the form of process data. Fig. 4 summarizes the model algorithm. The steps in the formulation of a model are described below.

- First, the LabVIEW™ PID controller output (-100 to 100) is mapped to a value from 2.5 to 0 volts, due to the reverse action of "air-to-close" pneumatic control valve.
- If the controller output "u(k)" is less than or equal to its previous value "u(k-1)", i.e., u(k-1) ≥ u(k), then the process output is estimated from the path "CDA" for the corresponding value of controlled signal.
- If the controller output "u(k)" is greater than its previous value "u(k-1)",i.e., u(k-1) < u(k), then the process output is estimated from the path "ABC" for the corresponding value of controlled signal.
- A moving average FIR filter is placed right in front of the estimated process output. The number of points in the filter is optimized to get the best result.

In the present study, the dynamic model of a liquid-flow process due to hysteresis of a pneumatic control valve is done using a neural network and polynomial function to be discussed next.

3.1 Using Neural Network

A neural network (NN) is capable of modeling a non-linear plant or process or system. On the basis of supplied training data, NN learns (trains) the relationship between the process inputs and outputs [9].

In the present work, in order to understand the liquid-flow process characteristics, control signal is applied to generate an open loop response. The input signal is applied from 0 to 100% in ten steps, then from 100% to 0 in another ten steps. The input output data generated is saved for further use. Due to a control valve, the liquid-flow process has shown hysteresis behaviour. NN is used for modeling a nonlinear liquid-flow process in open loop along the forward and backward motion of valve stem. A simple feed-forward NN of two layers (hidden and output) is used. For hidden layer thirty nodes and for output layer one node are chosen to achieve the goal error (mean square of error). Tan-sigmoid activation functions (*transig*) are used in the hidden layer and linear transfer function (*purelin*) is used in the output layer. The gradient descent algorithm is used as a basic learning scheme. Backpropagation algorithm is used to minimize the error. The neural network toolbox of MATLAB® R2008a is used to simulate a liquid-flow process model. The network is trained for the both paths and the two curves are imposed on a same graph. The hysteresis curve of a liquid-flow process model is depicted in Fig. 3.

3.2 Using General Polynomial Function

A polynomial function of a general form described by the below equation is used to estimate the dynamic hysteresis of a liquid-flow process.

$$f_i = \sum_{j=0}^{m} a_j x_i^j \qquad (1)$$

where *f* represents the output sequence *Best Polynomial Fit*, *x* represents the input sequence **X**, a_j represents the *Polynomial Coefficients*, and *m* is the *polynomial order*.
The *mse* (mean squared error) is calculated using the following equation:

$$mse = \frac{1}{n}\sum_{i=0}^{n-1} w_i (f_i - y_i)^2 \qquad (2)$$

where *y* represents the input sequence **Y**, w_i is weight, and *n* is the number of data points.

A LabVIEW™ code is developed for the function approximation of hysteresis of a liquid-flow process by using the input and output data of the process. The best polynomial fit for the forward motion of pneumatic valve stem, from open state to close state along the path ABC, is estimated with the mse = 1.577E-19. The relation evolved can be described by the following equation.

$$y = +192.000E{+}0 + 334.954E{+}0x - 3.148E{+}3x^2 + 12.122E{+}3x^3 - 26.874E{+}3x^4 + 35.751E{+}3x^5 - 29.562E{+}3x^6 + 15.340E{+}3x^7 - 4.863E{+}3x^8 + 861.099E{+}0x^9 - 65.305E{+}0x^{10} \qquad (3)$$

For the reverse motion of pneumatic valve stem along the path CDA, the best polynomial fit is developed with mse = 7.885E-20. The input-output relation can be described by the below equation.

$$y = +192.000E{+}0 - 116.700E{+}0x - 1.220E{+}3x^2 + 5.453E{+}3x^3 - 12.256E{+}3x^4 + 16.414E{+}3x^5 - 13.721E{+}3x^6 + 7.228E{+}3x^7 - 2.333E{+}3x^8 + 421.520E{+}0x^9 - 32.652E{+}0x^{10} \qquad (4)$$

4. REAL TIME RESULTS

Conventional Proportional plus Integral (PI) controller is used to control the Liquid-flow process in real time. The NI based hardware and software (LabVIEW™ PDS, version 7.1 & PID Toolkit, version 1.0) are used for real time implementation of measurement and control. The block diagram of the LabVIEW™ based code for PI Controller is shown in Fig.5.

4.1 Performance criterion

For controlling the flow of liquid through a pipe in the process control unit, the preferences of performance criteria, for the present work, are minimizing the settling time (2% band), overshoot and rise time.

4.2 Settings Used

The main settings that have to be done in the system are *set-point* and *disturbance*. The settings of these two are kept same for the whole experiment for carrying out the comparison of the readings. The flow-rate setpoint is kept 80 LPH and 140 LPH, respectively.

4.3 Conventional PI controller response to Setpoint Changes in real time

The conventional PID controller is tuned using Ziegler Nichol's method. The performance of the conventional PI

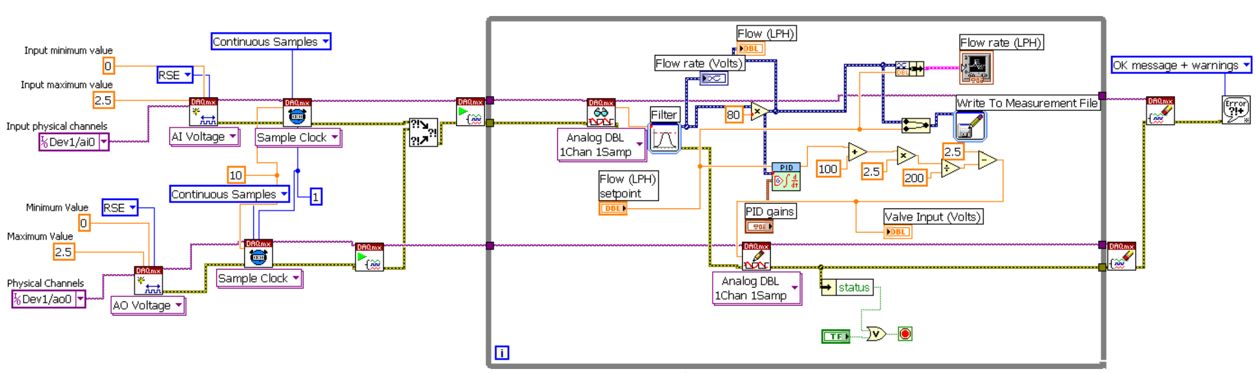

Fig. 5. LabVIEW Block Diagram of PI Controller in real time.

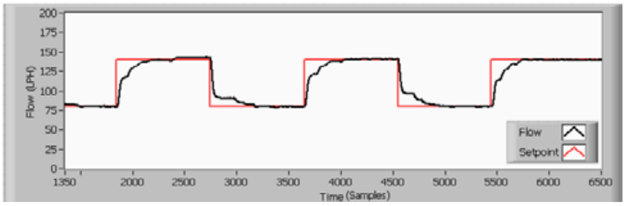

Fig. 6. Real time response of PI Controller

controller is the best among other conventional ones. Its real time response is shown in Fig. 6. The settings of parameters for this controller are given below. Proportional Constant (K_c) = 0.455; Integral Time Constant (τ_i) = 0.1 min; Setpoint = 80 & 140 LPH. No overshoot is observed, while settling time is 32.5 sec and rise time is 21.1 sec.

5. SIMULATION RESULTS

Feedback control configuration is simulated using the liquid-flow process model developed earlier. Simulation is carried out using NI software (LabVIEW™ & PID Toolkit) and MathWorks™ (MATLAB® R200a & Neural Network Toolbox™). The direction of motion of stem is estimated based upon the two successive values of the controller output. Once the direction of stem travel is detected, the corresponding curve of hysteresis of a liquid-flow process model is chosen to estimate the current value of process variable for the input to the process. A moving-average FIR filter is used for smoothing the process variable data. It is optimized for 45 points to get the best results. The sampling rate is chosen same as in real time.

5.1 Using Neural Network Based Model

Neural network toolkit is not available with LabVIEW™ software. Thus MATLAB® is called in LabVIEW™ to simulate the liquid-flow process. Performance criteria and all other settings are kept same as in real time. The backpropagation algorithm is used to develop the NN based model of a liquid-flow process due to the hysteresis of a pneumatic control valve. NN architecture is shown in Fig. 7. The detail of model training is given in Table 2. The weights and bias of the hidden layer of trained NN are shown in appendix, Tables 4 and 5. The NN training performance of path "ABC" and "CDA" are shown in Figs. 8 and 9.

Table 2 NN training details

	Path "ABC" / Path "CDA"	
No. of neurons	Hidden layer	30
	Outer layer	1
Learning rate	0.05	
Activation Function	Hidden layer "f^1"	Tansig
	Outer layer "f^2"	Linear
Error goal	1e - 10	

5.1.1. PI Controller Response to Set-point Changes

The settings of parameters for the PI controller are chosen

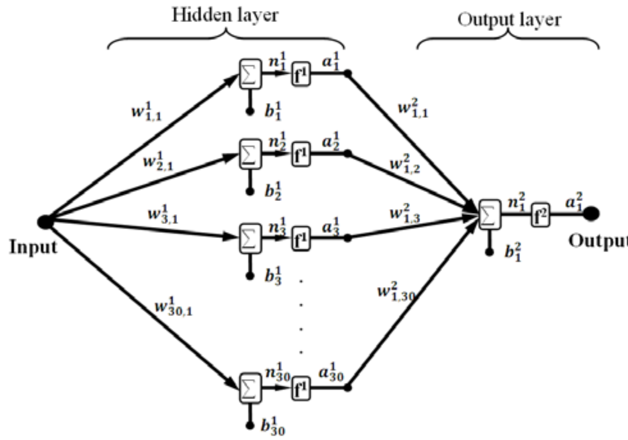

Fig. 7. NN architecture

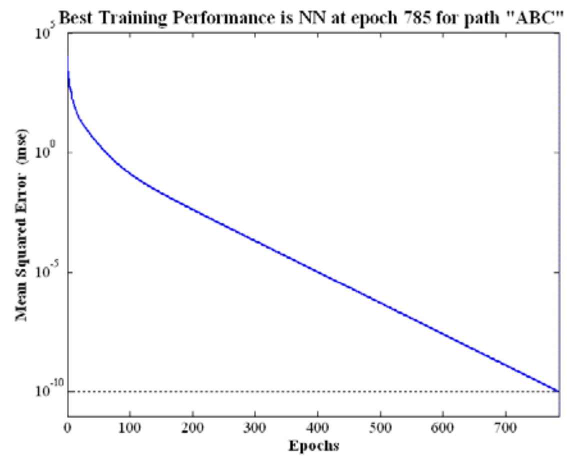

Fig. 8. NN Training performance of path "ABC"

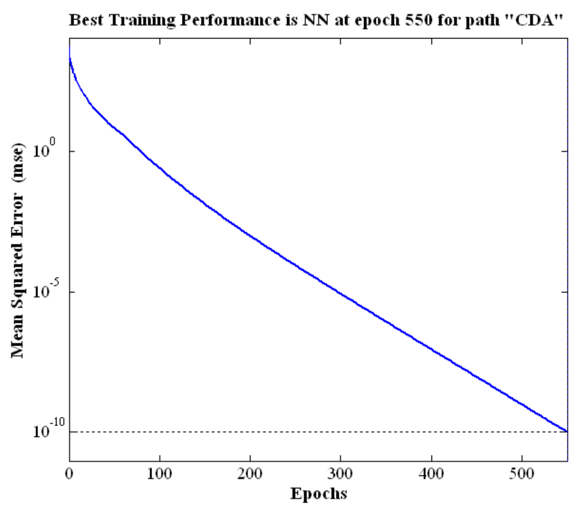

Fig. 9. NN Training performance of path "CDA"

same as in real time. The response of the PI controller is shown in Fig. 10. No overshoot is observed, while settling time is 32.2 sec and rise time is 20.5 sec. It is very close to the real time result. The closeness of the real time and simulation results verify the accuracy of the dynamic modeling of hysteresis of a liquid-flow process using neural network.

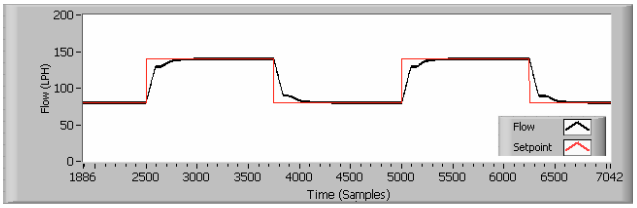

Fig. 10. Simulated response of PI Controller using an NN based model.

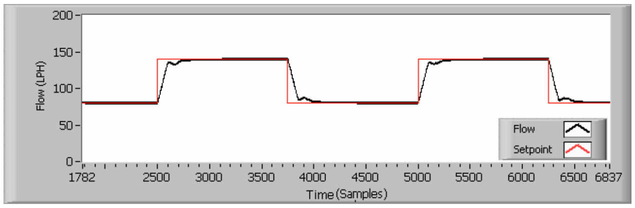

Fig. 11. Simulated response of PI Controller using a polynomial model

5.2 Using Polynomial Function Based Hysteresis Model

Formula node vi (virtual Instrumentation), available in the LabVIEW™ , is used to simulate the Polynomial Function based hysteresis of the liquid-flow process model. Performance criteria and all other settings are kept same as in real time.

5.2.1. PI Controller Response to Setpoint Changes

The settings of parameters for the PI controller are chosen same as in real time. The response of the PI controller is shown in Fig. 11. No overshoot is observed, while settling time is 33.5 sec and rise time is 19.9 sec. It is quite close to the real time result. The proximity of the real time and simulation results verifies the exactness of the dynamic modeling of hysteresis of a liquid-flow process using a polynomial function.

Table 3 Comparison of real time and simulation results

Conventional PI Controller	Settling Time 2 % (sec.)	% Overshoot	Rise Time (sec.)
In real time	32.5	--	21.0
In simulation using NN based model	32.2	--	20.5
In simulation using Polynomial based model	33.5	--	19.9

6. Conclusion

The dynamic modeling of hysteresis of a liquid-flow process is successfully done using neural network and general polynomial function. The validation of proposed models is carried out by comparing the real time and simulation results in a closed loop. Conventional PI controller is used in feedback configuration both in real time and simulation. The performance of the controller is evaluated to changes in setpoint. Simulation is done by using the proposed process models, with keeping all the settings and performance criteria same as in real time. It is observed that simulation results are almost matching with the real time results. From Table 3 it is marked that in real time, settling time and rise time are 32.5 sec and 21.1 sec, respectively. While in simulation with NN based model it is 32.2 sec and 20.5 sec and for polynomial function based model it is 33.5 sec and 19.9 sec, respectively. Among the simulation results, the NN based model shows better performance.

It is noted that due to a pneumatic control valve, the open loop response of the liquid-flow process is showing hysteresis behaviour. While in a closed loop, the process is showing the averaging of the process variable along the pneumatic control valve motion. It is verified by the closeness of the real time and simulation results. In simulation, the moving-average FIR filter is used for smoothing the process variable data after the proposed model. It is optimized for 45 points to get the finest results. Therefore the proposed dynamic model of hysteresis of a liquid-flow process depicts the internal behaviour of the process due to equal percentage pneumatic control valve having hysteresis.

The overall system performance is realized using the quality hardware for the measurement and state of the art software tools like LabVIEW™ with associated add-on modules and MATLAB® R200a and Neural Network Toolbox™.

ACKNOWLDGEMENTS

Authors would like to thank Institute for providing excellent experimental facilities in the Advanced Process Control Lab for research.

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Table 4 Weights and bias values for path "ABC"

Hidden layer				Outer layer			
Weights		Bias		Weights		Bias	
$w^1_{1,1}$	-15.2325	b^1_1	91.3470	$w^2_{1,1}$	17.4804	b^2_1	20.3913
$w^1_{2,1}$	28.4566	b^1_2	-83.1609	$w^2_{1,2}$	-15.5544		
$w^1_{3,1}$	33.2394	b^1_3	-78.3657	$w^2_{1,3}$	-3.4814		
$w^1_{4,1}$	27.5237	b^1_4	-78.0109	$w^2_{1,4}$	-15.3586		
$w^1_{5,1}$	33.2724	b^1_5	-72.5594	$w^2_{1,5}$	-2.1821		
$w^1_{6,1}$	33.5120	b^1_6	-69.5612	$w^2_{1,6}$	-1.3432		
$w^1_{7,1}$	-25.5500	b^1_7	70.2252	$w^2_{1,7}$	10.3333		
$w^1_{8,1}$	-33.5986	b^1_8	63.7248	$w^2_{1,8}$	1.9617		
$w^1_{9,1}$	-33.8710	b^1_9	60.6727	$w^2_{1,9}$	2.6328		
$w^1_{10,1}$	34.1682	b^1_{10}	-57.6064	$w^2_{1,10}$	-3.9093		
$w^1_{11,1}$	-33.6071	b^1_{11}	55.0303	$w^2_{1,11}$	3.7810		
$w^1_{12,1}$	35.0388	b^1_{12}	-51.1787	$w^2_{1,12}$	-3.4265		
$w^1_{13,1}$	-34.6266	b^1_{13}	48.5569	$w^2_{1,13}$	3.3059		
$w^1_{14,1}$	33.6105	b^1_{14}	-46.3371	$w^2_{1,14}$	-3.9054		
$w^1_{15,1}$	-35.3977	b^1_{15}	42.0101	$w^2_{1,15}$	4.6617		
$w^1_{16,1}$	-34.2082	b^1_{16}	40.0651	$w^2_{1,16}$	4.0247		
$w^1_{17,1}$	-33.6150	b^1_{17}	37.6412	$w^2_{1,17}$	4.7948		

$w^1_{18,1}$	35.3524	b^1_{18}	-33.0062	$w^2_{1,18}$	-6.1892		
$w^1_{19,1}$	-34.0407	b^1_{19}	31.4213	$w^2_{1,19}$	6.5173		
$w^1_{20,1}$	-33.6100	b^1_{20}	28.9531	$w^2_{1,20}$	5.9264		
$w^1_{21,1}$	34.6932	b^1_{21}	-24.6114	$w^2_{1,21}$	-6.9990		
$w^1_{22,1}$	33.7208	b^1_{22}	-23.0113	$w^2_{1,22}$	-6.2702		
$w^1_{23,1}$	33.6091	b^1_{23}	-20.2581	$w^2_{1,23}$	-4.8923		
$w^1_{24,1}$	34.0935	b^1_{24}	-16.3923	$w^2_{1,24}$	-5.9339		
$w^1_{25,1}$	-33.6291	b^1_{25}	14.4244	$w^2_{1,25}$	4.5552		
$w^1_{26,1}$	33.6112	b^1_{26}	-11.5417	$w^2_{1,26}$	-3.8022		
$w^1_{27,1}$	34.1760	b^1_{27}	-6.3855	$w^2_{1,27}$	-1.1252		
$w^1_{28,1}$	-33.6395	b^1_{28}	5.6332	$w^2_{1,28}$	-0.9698		
$w^1_{29,1}$	33.6001	b^1_{29}	-2.3570	$w^2_{1,29}$	0.1334		
$w^1_{30,1}$	-33.6000	b^1_{30}	-3.4314	$w^2_{1,30}$	-18.3998		

Table 5 Weights and bias values for path "CDA"

Hidden layer				Outer layer			
Weights		Bias		Weights		Bias	
$w^1_{1,1}$	25.2711	b^1_1	-87.3316	$w^2_{1,1}$	-19.5398	b^2_1	21.4704
$w^1_{2,1}$	27.5946	b^1_2	-83.5056	$w^2_{1,2}$	-17.5876		
$w^1_{3,1}$	-33.3174	b^1_3	78.3316	$w^2_{1,3}$	1.9702		
$w^1_{4,1}$	26.6246	b^1_4	-78.4105	$w^2_{1,4}$	-19.4089		
$w^1_{5,1}$	33.2960	b^1_5	-72.5489	$w^2_{1,5}$	-0.1019		
$w^1_{6,1}$	-33.4469	b^1_6	69.5937	$w^2_{1,6}$	-0.0546		
$w^1_{7,1}$	-29.6307	b^1_7	68.5100	$w^2_{1,7}$	-2.0183		
$w^1_{8,1}$	33.5809	b^1_8	-63.7337	$w^2_{1,8}$	-0.4965		
$w^1_{9,1}$	33.5533	b^1_9	-60.8543	$w^2_{1,9}$	0.7673		
$w^1_{10,1}$	33.4812	b^1_{10}	-57.9989	$w^2_{1,10}$	-1.1158		
$w^1_{11,1}$	-33.5993	b^1_{11}	55.0348	$w^2_{1,11}$	0.1395		
$w^1_{12,1}$	34.1769	b^1_{12}	-51.7533	$w^2_{1,12}$	-0.6781		
$w^1_{13,1}$	33.9755	b^1_{13}	-48.9911	$w^2_{1,13}$	-1.2182		
$w^1_{14,1}$	-33.6060	b^1_{14}	46.3405	$w^2_{1,14}$	2.3917		
$w^1_{15,1}$	34.9027	b^1_{15}	-42.4061	$w^2_{1,15}$	-2.4651		
$w^1_{16,1}$	-33.9673	b^1_{16}	40.2578	$w^2_{1,16}$	2.6083		
$w^1_{17,1}$	-33.6072	b^1_{17}	37.6483	$w^2_{1,17}$	2.5504		
$w^1_{18,1}$	35.1950	b^1_{18}	-33.1636	$w^2_{1,18}$	-4.0495		
$w^1_{19,1}$	33.9301	b^1_{19}	-31.5320	$w^2_{1,19}$	-4.4561		
$w^1_{20,1}$	33.6080	b^1_{20}	-28.9555	$w^2_{1,20}$	-4.3982		
$w^1_{21,1}$	34.9125	b^1_{21}	-24.3190	$w^2_{1,21}$	-6.2752		
$w^1_{22,1}$	-33.7549	b^1_{22}	22.9659	$w^2_{1,22}$	6.2221		
$w^1_{23,1}$	33.6162	b^1_{23}	-20.2439	$w^2_{1,23}$	-5.5644		
$w^1_{24,1}$	34.7042	b^1_{24}	-15.1707	$w^2_{1,24}$	-8.1558		
$w^1_{25,1}$	33.7173	b^1_{25}	-14.2476	$w^2_{1,25}$	-7.8382		
$w^1_{26,1}$	33.6487	b^1_{26}	-11.3923	$w^2_{1,26}$	-7.0921		
$w^1_{27,1}$	34.2966	b^1_{27}	-5.9037	$w^2_{1,27}$	-9.9144		
$w^1_{28,1}$	-33.6828	b^1_{28}	5.4635	$w^2_{1,28}$	8.8035		
$w^1_{29,1}$	33.6005	b^1_{29}	-3.1673	$w^2_{1,29}$	-8.8646		
$w^1_{30,1}$	-33.6000	b^1_{30}	-3.6327	$w^2_{1,30}$	-19.5228		

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