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Position Control of a Pneumatic Valve Using Nonlinear Model Predictive Control Based on Kalman Filter

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ABSTRACT: The paper proposes the control algorithm for position control for a pneumatic valve using the predictive control based on Kalman filter. The difference between the actual valve opening and desired valve opening is caused by the stiction dynamic of the valve. To model the valve with stiction in the piecewise linearizing form, the higher order transfer function is used. The Kalman filter then is used for determining the states of the valve, thereby the predictive controller with predictive window is slided respect to the time axis. The optimal control signal for controlling the valve position is also determined directly in each sampling cycle. The experiment results indicate that the proposed control algorithm works well, and the delay phenomenon caused by the stiction is reduced.

KEYWORDS: Pneumatic valve control, valve position control, stiction phenomenon, model predictive control, Kalman filter, nonlinear valve model.

INTRODUCTION

Pneumatic valve is the popular equipment in the process control field which is used for adjusting the flow rate of the materials to the manufacturing process (fluid, air, crude oil …). The precisely control problem of valve position is investigated in few recent decades, however most methods use the mechanical positioning controllers which are available with the valve[1,2]. The control performance (control of flow rate using valve) is depended on the accuracy of the valve opening, but this characteristic is totally depended on the working mode (fast, slow,... opening of the valve) and non-linear characteristics of the valve for instance delay, jumpslip, stiction phenomena [3-5]. Nowaday, the valve is a subject mostly used in the industry, therefore any development, even just a little, can improve the control performance of the total process.

The performance of the mechanical positioning controllers is quite good in cases of the slowly opened valve or linear valve characteristics, otherwise such as fast, large openning range, and high frequency opening in which transient processes appear frequently, the control performance is limited because the non-linear dynamic characteristics arise more. The delay, gap, stiction, and sliding phenomena most appears in the short transient process, and they are very hard to determine explicitly, and may not approximates precisely by using identification tools. There are two solutions for limiting the sticky phenomena which is to develop technology of manufacturing the valve and propose the suitable control methods. Figure 1 illustrates the model of the pneumatic valve and the stiction phenomenon.

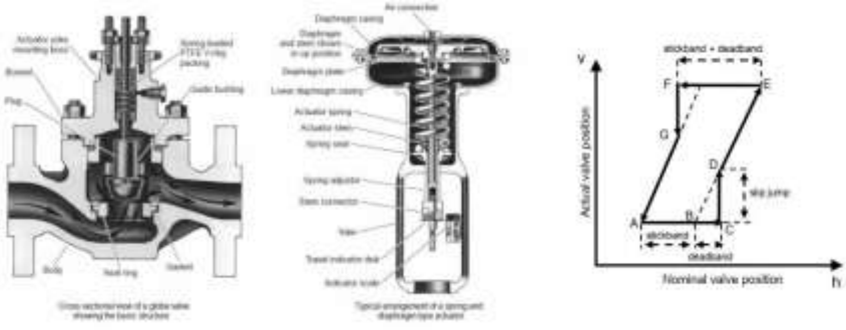

Figure 1. The pneumatic valve and stiction phenomenon

There are recently many researches about establishing the non-linear dynamic model of pneumatic valves [4,6,7]. These dynamic models describe almost exactly the dynamic characteristics of the valve, but that works do not contribute much in designing the controllers, because they don't satisfy some necessary assumptions of the design in reality, especially uniformity of this models. In order to eliminate these problems, the dynamic model of the valve need to be approximated with high accuracy to satisfy the requirements of the control design problems. Due to the advantages of the predictive controller [8-12] which are an ability to predict the output of the future process, and the control signal then is determined optimally via constraints. The nonlinear dynamics of the valve in the working process will be defined, then the control signal is determined such that the valve position is controlled most exactly. The states of the valve providing to the controller are estimated by using Kalman filter [13,14,23].

Based on this idea, the non-linear dynamic model of the valve is piecewisely linearized in each sampling time. Control signals, valve's states are determined completely in a moving horizon estimation window. The experimental results indicate that the valve position is controlled precisely in the transient time. The paper is organized as: the introduction is shown in section 1, the model of pneumatic valve with nonlinear dynamics is described in section 2, section 3 presents the non-linear model predictive control based on state observer for pneumatic valve with nonlinear dynamics, the experimental results are given in section 4. Finally, The discussions are mentioned in section 5.

THE MODEL OF PNEUMATIC VALVE WITH NONLINEAR DYNAMICS

Assume that the valve is shown in Figure 1, without the stiction phenomena, we have the equation describing the dynamics of the valve as

$$\begin{cases} m\dfrac{d^2h}{dt^2}+d\dfrac{dh}{dt}+kh+\left(\dfrac{c}{h_{\max}}\right)sign\left(h\right)+\dfrac{F_p}{h_{\max}}=\dfrac{A}{h_{\max}}p \\ q=\sqrt{h}Q\sqrt{\dfrac{\Delta P}{\rho}} \end{cases} \tag{1}$$

in which: $h = h_r / h_{max}$, h_{max} is maximum valve opening; h_r, h are the real valve opening (0 – 100 %) and the valve opening level, respectively. They are converted from $0-1$, in which 0 indicates a completely closing state, and 1 shows a completely opening state; p is the actuator air pressure (the pressure acting on the valve's chamber) or the value input signal; m is a total weight of the valve and the valve's closure member; d is a attenuating factor due to the speed of the motion of valve's stem and valve's closure member including the dynamic friction; c is a factor of the static friction; A is an area of the valve's membrane; F_p is a dissipated force; q is the process liquid flow pass though valve, ΔP is the fluid pressure drop across the valve; Q is a flow rate of the process passing through the valve per a unit of the fluid pressure drop; ρ is a density of the liquid flow passing through the valve. Nonlinear components in the system are $sign(h)$ function, F_p and $\sqrt{h}$ (element specializing for the fast opening valve).

If the sticky phenomena are considered, the actual valve opening level is differed from the valve opening level h . Therefore nonlinear dynamic model (1) of the valve could be:

$$\begin{cases} m\dfrac{d^2h}{dt^2}+d\dfrac{dh}{dt}+kh+\left(\dfrac{c}{h_{\max}}\right)sign\left(h\right)+\dfrac{F_p}{h_{\max}}=\dfrac{A}{h_{\max}}p \\ v=\phi\left(h\right) \\ q=\sqrt{v}Q\sqrt{\dfrac{\Delta P}{\rho}} \end{cases} \tag{2}$$

in which the stiction phenomenon makes the actual valve opening level v differed from the valve opening level h by the $\phi(h)$ function. The reasons of the stiction phenomenon are caused by the static friction in the starting motion stage. If the valve is in the position A, we need to increase the valve opening level. Firstly, because of the static friction, there are a dead range or a gap AB (deadband), and a stickband BC. When passing over these ranges, the forces acting on the motion mechanism suddenly increase under the acting of the saving power that causes the slipjump phenomena of the valve to the position D. If the process flow rate is greater than the setpoint on DE displacement, the valve will be closed with all above phenomenons and cause the hysteresis. Those phenomena are all called stiction phenomena which hinders the achievement of good performance of control valves [15].

The general model of the process from the pressure p to actual valve opening level v and flow rate is non uniformity. This non uniformity stays on hysteresis region of the fuction $v = \phi(h)$, therefore it is not suitable for the analysis and control problems. To overcome this, we use the approximated linear dynamics based on converting function $v = \phi(h)$ into uniformity function. The work of approximating the function $v = \phi(h)$ was investigated in some previous research documents. The authors in [16] use the data-driven model of stiction for converting the function $v = \phi(h)$ to complex gain factor, and in the documents [17,18] the approximation the function $v = \phi(h)$ into a polynomial that means approximating the nonlinear parts having static dynamics is presented. The function $v = \phi(h)$ is approximated to the higher order transfer function in order to fit the goal of using the predictive control algorithm. The Figure 2 illustrates that idea.

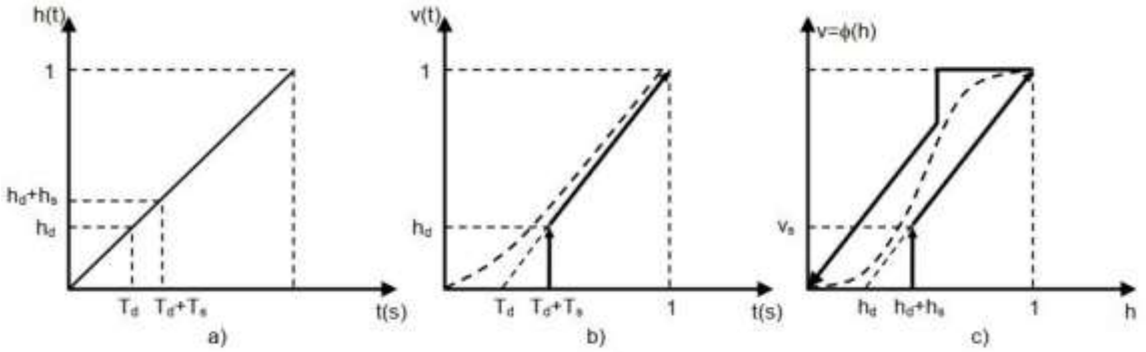

Figure 2. The linear dynamic approximation of the stiction phenomenon of pneumatic valve

Assume that the valve opening level h increases steadily from 0 to 1 as shown in Figure 2.

$$h(t) = t \tag{3}$$

At that time the actual valve opening level $v(t)$ with the stiction phenomena is a solid line, we approximate this line to the continuous dashed line shown in Figure 2. The equation of this line is described by the following equation:

$$v(t) \approx \beta \int_0^t \left(\tau - nT + \sum_{i=1}^{n} \frac{(n+1-i)\,\tau^{i-1} e^{-\frac{\tau}{T}}}{T^{i-2}(i-1)!} \right) d\tau \tag{4}$$

in which $T \approx T_d + T_s$ is the time for $v(t)$ passing over the deadband (gap and sticky-sliding interval) in the stiction period of the valve, $\beta = 1/(1-T_d) \approx 1$ is a propotional gain. Arcoding to [4], the greater n, the less the error between the dashed line $v(t)$ given by equation (4) and the solid line. Converting (3) and (4) into Laplace domain we have:

$$H(s) = \frac{1}{s^2} \text{ and } V(s) = \frac{\beta}{s^2 (1+Ts)^n} \tag{5}$$

where $H(s)$ and $V(s)$ are Laplace transforms of the $h(t)$ and $v(t)$. Therefore the transfer function of the stiction phenomena is described as following equation:

$$G(s)=\frac{V(s)}{H(s)}=\frac{\beta}{(1+Ts)^n} \tag{6}$$

The stiction phenomena is illustrated in Figure 2c. After approximating the stiction component, the dynamic of the valve system written in time domain is:

$$\begin{cases} m\dfrac{d^2h}{dt^2}+d\dfrac{dh}{dt}+kh+\left(\dfrac{c}{h_{\max}}\right)sign(h)+\dfrac{F_p}{h_{\max}}=\dfrac{A}{h_{\max}}p \\ v=L^{-1}\left\{\dfrac{\beta}{(1+Ts)^n}\right\} \\ q=\sqrt{v}Q\sqrt{\dfrac{\Delta P}{\rho}} \end{cases} \tag{7}$$

where $L^{-1}\{\ \}$ stands for the inverse Laplace transform. With the assumption of $n=2$, the time interval $T\approx T_d+T_s$ is small enough, determining the inverse Laplace transform, the model (7) becomes:

$$\begin{cases} m\dfrac{d^2h}{dt^2}+d\dfrac{dh}{dt}+kh+\left(\dfrac{c}{h_{\max}}\right)sign(h)+\dfrac{F_p}{h_{\max}}=\dfrac{A}{h_{\max}}p \\ T^2\dfrac{d^2v}{dt^2}+2T\dfrac{dv}{dt}+v=\beta h \\ q=\sqrt{v}Q\sqrt{\dfrac{\Delta P}{\rho}} \end{cases} \tag{8}$$

Let the state variable is $\underline{x}=(x_1=h, x_2=dh/dt, x_3=v, x_4=dv/dt)$, a pressure signal is defined via I/P converter, hence the model of the valve has the current signal input (I) and the flow rate output (q):

$$\frac{d\underline{x}}{dt}=\underline{f}(\underline{x},I)=\begin{cases} x_2 \\ -\dfrac{k}{m}x_1-\dfrac{d}{m}x_2-\dfrac{c}{mh_{\max}}sign(x_1)-\dfrac{F_p}{h_{\max}}+KI \\ x_4 \\ -\dfrac{1}{T^2}x_3-\dfrac{2}{T}x_4+\beta x_1 \end{cases}$$
$$q=\sqrt{x_3}Q\sqrt{\frac{\Delta P}{\rho}} \tag{9}$$

in which $K=Ak/h_{\max}$, with k is a propotional gain of the I/P converter.

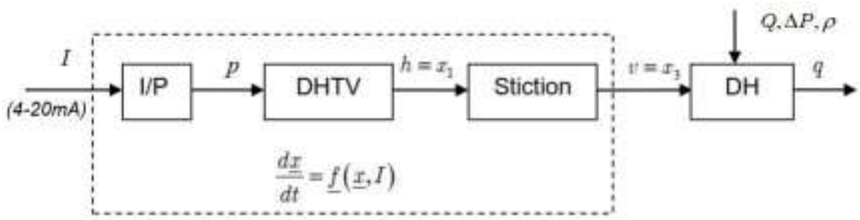

Figure 3. The proposed model of pnematic valve

As shown in Figure 3, the model (9) is a dynamic model of the valve with non-linear dynamic components, and stiction phenomena are considered. This model will be used to design the controller for stabilizing the valve position v, and the predictive control method is applied based on state variable observer.

NONLINEAR MODEL PREDICTIVE CONTROL BASED ON STATE OBSERVER FOR PNEUMATIC VALVE WITH NONLINEAR DYNAMICS

The control scheme is shown in Figure 4. in which the inner loop is a valve position control loop, and the outer loop is the process flow rate control loop. In this paper, the inner loop is focused on, and the outer loop can be use a few popular controller types such as PI or PID for adjusting flow rate.

The output of the inner loop is an actual valve position v, and it might be derived from equation (9) as following:

$$\begin{cases} \dfrac{d\underline{x}}{dt} = \underline{f}\left(\underline{x}, I\right) \\ y = v = g\left(\underline{x}\right) = x_3 \end{cases} \tag{10}$$

Valve positioning control using the predictive control with state feedback

Valve positioning control using the predictive control with state feedback is designed based on piecewise linearizing the nonlinear system (10) corresponding to time axis and the movement of the predictive window illustrated in figure 5. In which H_k is a linear model used to predict the output $\hat{y}_{k+i}$ for the nonlinear system (10) which belongs to the present predictive window $\left[k, k+N\right]$. It means that $0 \le i \le N$, N is a length of the predictive window.

Let k is a sampling point, $k = 0 \to \infty$, sampling time T_a is small enough, the continuous system (10) is converted to:

$$\begin{cases} \underline{x}_{k+1} = \underline{f}\left(\underline{x}_k, I_k\right) \\ y_k = C\underline{x}_k \end{cases} \tag{11}$$

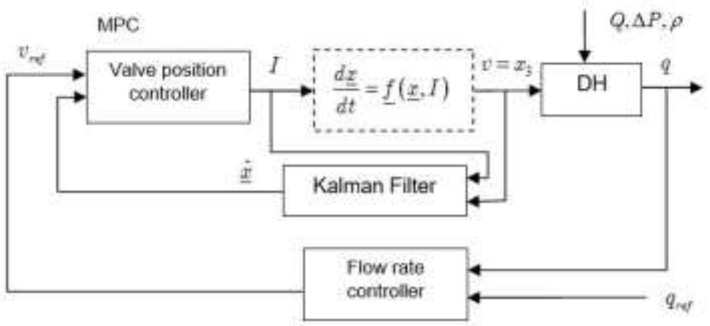

Figure 4. The control sheme using predictive control based on state observer for pneumatic valve

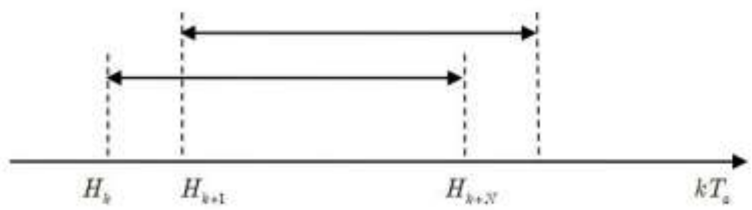

Figure 5. Illustration of predictive window

in which $C = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}$, $\underline{f}\left(\underline{x}_k, I_k\right)$ are the smooth vector, two time differentiable. At the present time $t = kT_a$, vector $\underline{f}\left(\underline{x}_k, I_k\right)$ could be approximated as a system of linear equations by integrating the Taylor chain on the neighborhood points $\underline{x}_{k-1}, I_{k-1}$ as the following equation:

$$\underline{f}\left(\underline{x}_k, I_k\right) \approx \underline{x}_k + A_k\left(\underline{x}_k - \underline{x}_{k-1}\right) + B_k\left(I_k - I_{k-1}\right) \tag{12}$$

where

$$A_k = \left.\frac{\partial \underline{f}}{\partial \underline{x}}\right|_{\underline{x}_{k-1}, I_{k-1}}, \quad B_k = \left.\frac{\partial \underline{f}}{\partial I}\right|_{\underline{x}_{k-1}, I_{k-1}}, \quad \underline{x}\{k\} = \underline{f}\left(\underline{x}_{k-1}, I_{k-1}\right) \tag{13}$$

Next, because $\underline{f}\left(\underline{x}_k, I_k\right)$ is two times differentiable, matrices A_k, B_k are continuous. Hence we have:

$$A_k \underline{x}_{k-1} + B_k I_{k-1} \approx A_{k-1}\underline{x}_{k-1} + B_{k-1} I_{k-1} = \underline{x}_k \tag{14}$$

Thus, at the time $t = kT_a$, non-linear system describing the dynamics of the valve is approximated by:

$$H_k : \begin{cases} \underline{x}_{k+1} = A_k \underline{x}_k + B_k I_k \\ y_k = C\underline{x}_k \end{cases} \tag{15}$$

Assume the state variables measured at the time k, and matrices A_k, B_k of the model H_k are constant matrices. Then, we use the linear model H_k (15) to predict the output signal $y_{k+i}, 0 \le i \le N$ on the present predictive window. From the predictive model (15) we have:

$$\begin{aligned} \underline{x}_{k+i} &= A_k \underline{x}_{k+i-1} + B_k I_{k+i-1} = A_k\left(A_k \underline{x}_{k+i-2} + B_k I_{k+i-2}\right) + B_k I_{k+i-1} \\ &= A_k^2 \underline{x}_{k+i-2} + A_k B_k I_{k+i-2} + B_k I_{k+i-1} \\ &= A_k^2\left(A_k \underline{x}_{k+i-3} + B_k I_{k+i-3}\right) + A_k B_k I_{k+i-2} + B_k I_{k+i-1} \\ &= A_k^3 \underline{x}_{k+i-3} + A_k^2 B_k I_{k+i-3} + A_k B_k I_{k+i-2} + B_k I_{k+i-1} \\ &\vdots \\ &= A_k^i \underline{x}_k + A_k^{i-1} B_k \underline{u}_k + \ldots + A_k B_k I_{k+i-2} + B_k I_{k+i-1} n \end{aligned} \tag{16}$$

and

$$y_{k+i} = C\underline{x}_{k+i} = CA_k^i \underline{x}_k + CA_k^{i-1} B_k \underline{u}_k + \ldots + CA_k B_k I_{k+i-2} + CB_k I_{k+i-1} \tag{17}$$

Assume that the symbol $\underline{\kappa} = col\left(I_k, I_{k+1}, ..., I_{k+N}\right)$ is used, thus all predictive output values y_{k+i} will be written as:

$$\underline{y} = \begin{pmatrix} y_k \\ y_{k+1} \\ \vdots \\ y_{k+N} \end{pmatrix} = \underbrace{\begin{pmatrix} CA_k \\ \vdots \\ CA_k^N \end{pmatrix}}_{\underline{\underline{\Delta}}F} \underline{x}_k + \underbrace{\begin{pmatrix} CB_k & \Theta & \cdots & \Theta \\ \vdots & \vdots & \ddots & \vdots \\ C_k A_k^{N-1} B_k & C_k A_k^{N-2} B_k & \cdots & CB_k \end{pmatrix}}_{\underline{\underline{\Delta}}F} \underline{\kappa} = E\underline{x}_k + F\underline{\kappa} \tag{18}$$

Because $\underline{x}_k$ is known, $\underline{y}$ in the equation (18) is just depended on $\underline{\kappa}$ in which I_k is contained. In order to determine the present input I_k at $t = kT_a$ such that the system tracks the desired signal $\left\{v_k^{ref}\right\}$, we establish the tracking error function in all present predictive windows as (19).

$$\underline{e} = \begin{pmatrix} v_k^{ref} \\ v_{k+1}^{ref} \\ \vdots \\ v_{k+N}^{ref} \end{pmatrix} - \underline{y} = \begin{pmatrix} v_k^{ref} \\ v_{k+1}^{ref} \\ \vdots \\ v_{k+N}^{ref} \end{pmatrix} - E\underline{x}_k - F\kappa = \underline{z} - F\underline{\kappa}, \text{with}\, \underline{z} = \begin{pmatrix} v_k^{ref} \\ v_{k+1}^{ref} \\ \vdots \\ v_{k+N}^{ref} \end{pmatrix} - E\underline{x}_k \tag{19}$$

For the purpose of minimizing the objective function about the predictive error, the objective function is written as (20)

$$\begin{aligned} J(\underline{\kappa}) &= \underline{e}^T \Lambda_k \underline{e} + \kappa^T L_k \underline{\kappa} = (\underline{z} - F\underline{\kappa})^T \Lambda_k (\underline{z} - F\underline{\kappa}) + \underline{\kappa}^T L_k \underline{\kappa} \\ &= \underline{z}^T \Lambda_k \underline{z} - 2\underline{z}^T \Lambda_k F \underline{\kappa} + \underline{\kappa}^T \left(F^T \Lambda_k F + L_k\right) \underline{\kappa} \xrightarrow[\underline{\kappa}]{} \min \\ \Leftrightarrow J'(\underline{\kappa}) &= -2\underline{z}^T \Lambda_k F \underline{\kappa} + \kappa^T \left(F^T \Lambda_k F + L_k\right) \underline{\kappa} \xrightarrow[\underline{\kappa}]{} \min \end{aligned} \tag{20}$$

There are two symmetric and positive definitive weights Λ_k, L_k, and they are arbitrary chosen. We will have an optimal solution in case of unconstraints $I_k \in \mathrm{I}$ as follow [10]:

$$\underline{\kappa}^* = \left(F^T \Lambda_k F + L_k\right)^{-1} F^T \Lambda_k \underline{z} \tag{21}$$

Thus, the control signal at the present time $t = kT_a$ is:

$$I_k = (1,0,...,0)\underline{\kappa}^* = (1,0,...,0)\left(F^T \Lambda_k F + L_k\right)^{-1} F^T \Lambda_k \underline{z} \tag{22}$$

The control algorithm:

Step 1: lets $k = 0$, and chooses $N = 2$.

Step 2: from the state $\underline{x}_k$ the matrices A_k, B_k are defined in (13), and matrices E, F are shown in (18), vector $\underline{z}$ is (19), Λ_k, L_k are chosen as sysmetrical and positive definitive matrices, we can choose $\Lambda_k = diag\left(\lambda_i^k\right)$ such that meets the conditions: $\lambda_i^k > \lambda_j^k > 0, j = 2,3,...,M, M = \dim(\underline{e})$.

Step 3: calculate the control signal I_k by equation (22) to control the system (\ref{Eq_11}) on the time interval that equals to the sampling time T_a.

Step 4: lets $k = k+1$, and comes back to **step 2.**

If the system has constraints about the control signal $I_k \in \mathrm{I}$, we need to use nonlinear programming QP or SQP [19] instead of using formula (22) in order to figure out $\underline{\kappa}^*$, and from that the parameter $I_k \in \mathrm{I}$ is determined.

State observer

In order to determine the state vector $\underline{x}_k$ for the control algorithm, we need to observe and define $\underline{x}_k$ via measuring the signals I_{k-1} and y_{k-1} by using the type-three Kalman filter. Defining left $\underline{x}_k^-$ and right $\underline{x}_k^+$ access points gives the actual value of $\underline{x}_k$:

$$\begin{aligned} \underline{x}_k^- &= \underline{f}_k\left(\underline{x}_{k-1}^+, I_{k-1}\right) \\ \underline{x}_k^+ &= \underline{x}_k^- + K_k\left(\underline{y}_k - C\underline{x}_k^-\right) \end{aligned} \tag{23}$$

in which $K_k = \arg\min M\left[\left(\underline{x}_k - \underline{x}_k^+\right)^2\right]$. The observing algorithm $\hat{\underline{x}}_k$ for the system (11) is [20,21]:

The observer algorithm

Step 1: Setting the initial condition $\hat{x}_0 = \underline{x}_k^+$ and P_0^+. Measuring $I_0, \underline{y}_0$. Lets $k = 1$.

Step 2: Choosing two weight matrices Λ_k, L_k as the symmetrical and positive definitive matrices.

Step 3: Calculating $\underline{x}_k^- = \underline{f}_k\left(\underline{x}_{k-1}^+, I_{k-1}\right)$, $F_{k-1} = \left.\frac{\partial \underline{f}_k\left(\underline{x}_{k-1}, I_{k-1}\right)}{\partial \underline{x}_{k-1}}\right|_{\underline{x}_{k-1}^+}$

$$\begin{aligned} P_k^- &= F_{k-1}P_{k-1}^+F_{k-1}^T + \Psi_{k-1} \\ K_k &= P_k^- C^T (CP_k^- C^T + \Phi_k)^{-1} \\ P_k^+ &= \left(I - K_k C\right)P_k^- \\ \underline{x}_k^+ &= \underline{x}_k^- + K_k\left(\underline{y}_k - C\underline{x}_k^-\right) \end{aligned}$$

Step 4: $\hat{\underline{x}}_k = \underline{x}_k^+$ is a observed state of the state $\underline{x}_k$ at the time k, lets $k = k+1$ and returns to **step 3.**

The output feedback and the ISS stability of the closed system

The control signal defining the valve position using observed states $\hat{\underline{x}}_k$ of $\underline{x}_k$ is determined by replacing $\hat{\underline{x}}_k$ to $\underline{x}_k$ in step 2 of the control algorithm. This is called the output feedback control based on the state observer.

Firstly, denotes I_k^* by equation

$$I_k^* = S^{PC}\left(\underline{x}_k\right) \tag{24}$$

This is the predictive controller with state feedback which makes the system (11) to be global asymptotic stable according to Lyapunov theory, it means that there exists a complex function:

$$\gamma_1\left(\left|\underline{x}_k\right|\right) \le V\left(\underline{x}_k, k\right) \le \gamma_2\left(\left|\underline{x}_k\right|\right) \tag{25}$$

satisfies

$$\begin{aligned} \Delta V &= V\left(\underline{x}_{k+1}, k+1\right) - V\left(\underline{x}_k, k\right) = V\left(\underline{f}\left(\underline{x}_k, I_k^*\right), k+1\right) - V\left(\underline{x}_k, k\right) \\ &= V\left(\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right), k+1\right) - V\left(\underline{x}_k, k\right) \le -\gamma_2\left(\left|\underline{x}_k\right|\right) \end{aligned} \tag{26}$$

in which, $\gamma_i\left(r\right), i = 1,2,3$ is a symbol of the class-K function. It means that real functions of real variables $r \ge 0$ increase monotonically, and $\gamma_i\left(0\right) = 0$, thus the problem of stability with the output feedback based on the separating principle [22] here is equivalent to the problem of the stability of the system.

$$\underline{x}_{k+1} = \underline{f}\left(\underline{x}_k, S^{PC}\left(\hat{\underline{x}}_k\right)\right) = \underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k + \underline{e}_k\right)\right) \tag{27}$$

in which $\underline{e}_k = \underline{x}_k - \hat{\underline{x}}_k$ is denoted for the tracking error observed at the time k.

Theorem 1: *The controller of the valve position (22) is the Lipchitz function. The system of equation (11) with a vector function* $\underline{f}\left(\underline{x}_k, I_k\right)$ *satisfy the Lipschitz condition and Kalman filter always exist the finite observed error, hence the predictive controller with the output feedback stabilizes ISS the system (11).*

Proof:

Because the assumption that the state feedback controller (22) meets the Lipchitz condition, we always have:

$$\left|S^{PC}\left(\hat{\underline{x}}_k\right) - S^{PC}\left(\underline{x}_k\right)\right| \le L_1\left|\underline{x}_k\right| \tag{28}$$

in which L_1 is Lipchitz constant of $I_k^* = S^{PC}\left(\underline{x}_k\right)$.

Besides, the controller (22) makes the system asymptotically stable, so it must have:

$$\left|\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right)\right| \le \beta\left(\left|\underline{x}_0\right|, k\right) \tag{29}$$

with $\beta \in KL$ is non-negative function. It increases monotonically with $\left|\underline{x}_0\right|$, and decreases monotonically with k.

Thus, when the function vector $\underline{f}\left(\underline{x}_k, I_k\right)$ meets the Liptchitz condition, it means:

$$\left|\underline{f}\left(x_k, \hat{I}_k\right) - \underline{f}\left(x_k, I_k\right)\right| \le L_2\left|\hat{I}_k - I_k\right| \tag{30}$$

with L_2 is the Lipchitz constant corresponding to $\underline{f}\left(\underline{x}_k, I_k\right)$, the state trajectory of the closed system controlled by the predictive control with the output feedback needs to satisfy:

$$\begin{aligned}\left|\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{\hat{x}}_k\right)\right)\right| &= \left|\left(\underline{x}_k, S^{PC}\left(\underline{\hat{x}}_k\right)\right) - \underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right) + \underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right)\right| \\ &\le \left|\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{\hat{x}}_k\right)\right) - \underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right)\right| + \left|\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right)\right| \\ &\le L_2\left|S^{PC}\left(\underline{\hat{x}}_k\right) - S^{PC}\left(\underline{x}_k\right)\right| + \left|\underline{f}\left(\underline{x}_k, S^{PC}\left(\underline{x}_k\right)\right)\right| \\ &\le L_2 L_1\left|\underline{e}_k\right| + \beta\left(\left|\underline{x}_0\right|, k\right)\end{aligned} \tag{31}$$

This proves that: when $\underline{e}_k = \underline{x}_k - \underline{\hat{x}}_k$ is limited, the state trajectory $\left\{\underline{x}_k\right\}$ of the closed system always lies in an attractive domain with diameter d that is not greater than:

$$d \le L_2 L_1 \sup_k \left|\underline{e}_k\right| \tag{32}$$

Otherwise, if the chain $\left\{\underline{e}_k\right\}$ is monotonically decreasing, the diameter d will be smaller.

EXPERIMENTAL RESULTS

The experimental setup is described by Figure 6. with the equipment including: pneumatic valve KOMOTO PVSET35, position sensor, pressure sensor, pressure stabilization controller, compressed air supplier, V/I converter, Lock up Valve, data collector dSpace 1104, computer with Matlab/Simulink and Control Desk softwares.

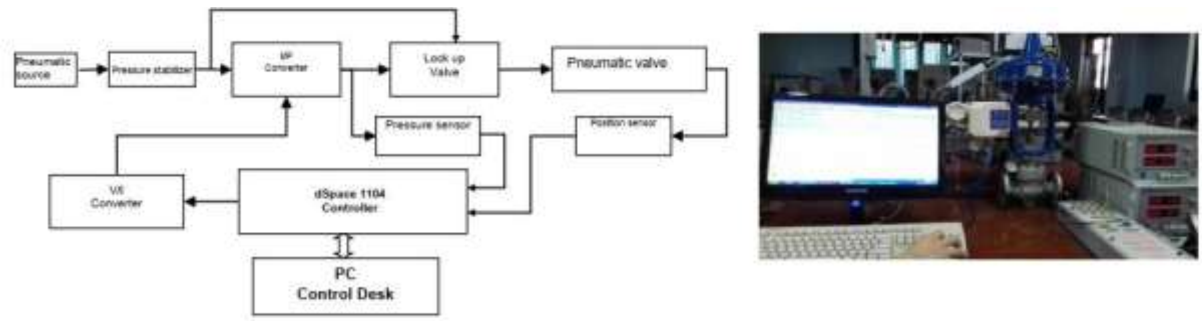

Figure 6. The scheme of the experimental system at 310TN building - Thai Nguyen University of Technology

The observing results of the h, $\dot{h}$, v, and $\dot{h}$

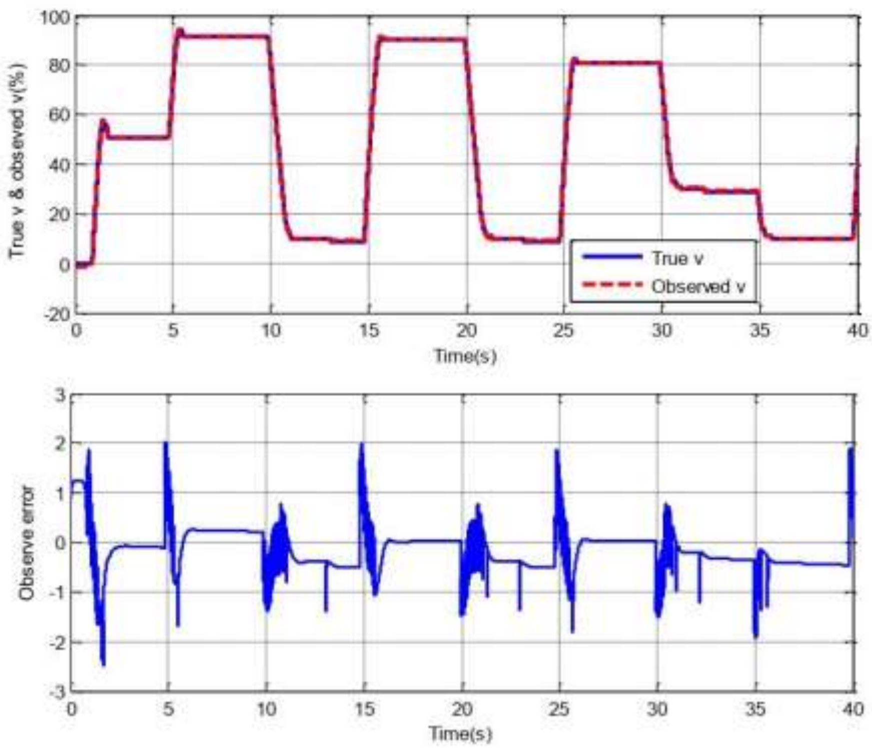

Figure 7. Value of v

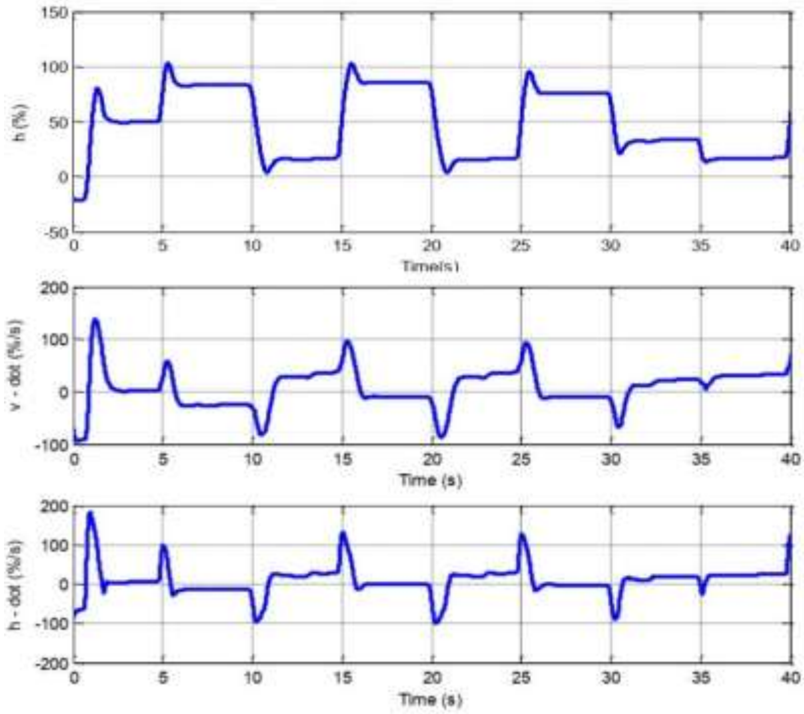

Figure 8. The observed value of h, $\dot{h}$, v

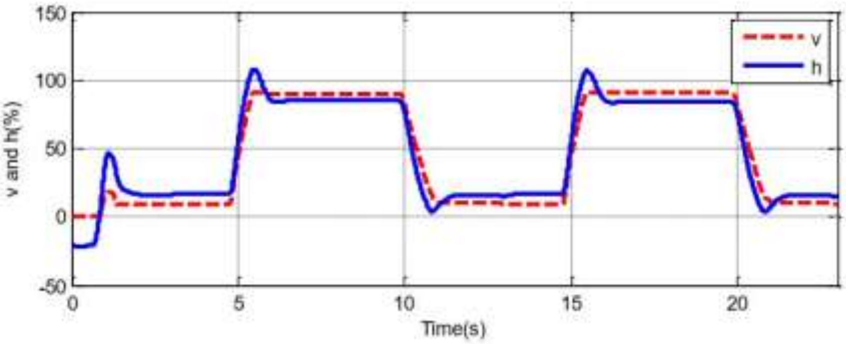

Figure 9. The diagram of h and v during time with the both sides of the open/close states increasing from 10 % to 90 %, then decreasing from 90 % to 10 % (the increasing/decreasing period is 10 [s]

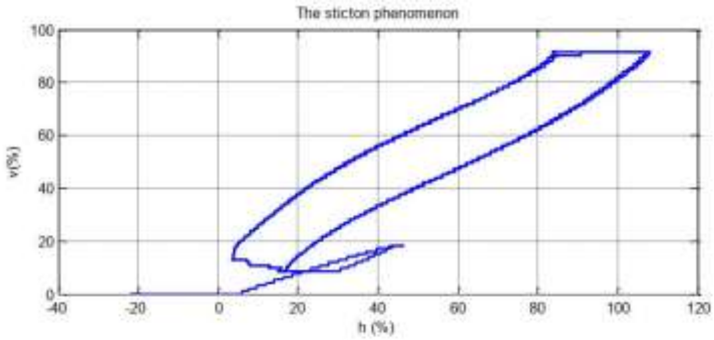

Figure 10. The stiction phenomenon of the valve in the experiment

Observing results of the h and v and their derivatives

Simulation result of the valve position is shown in Figure 7. It can be seen that the observed position v is tracked to the actual value of v accurately. The largest position error is 2.4 %. The largest error only occurs when the valve opens suddenly. At the steady state, this error is very small, about 1 %. Figure 8. shows the observed value of h, and the derivatives of h and v.

The results that determine the stiction phenomena of the valve:

The stiction phenomenon of the valve is shown in Figure 9. and Figure 10. It indicates that the delay of h and v via the acting orientation of the valve in comparision to the ideal characteristic. This phenomenon reflects the effects of the delay, gap, stiction, and slipjump of the pneumatic valve in the experiment.

The results when applying the predictive controller

After observing the values of h, v and the derivations of them, these values are sent to the predictive controller to perform the valve position controller. The results are indicated in Figure 9. The valve is controlled from the starting point 10 %, and increased up to 50 % after 5 $[s]$, and continuously increased up 90 % in next 5 seconds. The valve position suddenly decreases downward to 10 % at $(t=15[s])$ and remains to $(t=20[s])$, then slowly increases upward 90 % from $(t=20[s])$ to $(t=25[s])$. Finally the valve position is set to 50 % at $(t=30[s])$.

From the Figure 11. we can see that the actual valve position tracks well to the desired trajectory. The maximum time delay is 2 $[s]$, when the valve position switches from 90 % to 10 %. The overshoot reaches greatest (10%) at $(t=5[s])$. After that later open/close times do not occur overshoot, because at some first cycles the predictive controller does not predict exactly the actual valve position, and next cycles the accuracy of the observer increases therefore the predictive controller get the position of h and v more precise. These things help to eliminate the stiction phenomenon, hence get rid of the overshoot. The changes of h, $\dot{h}$ and $\dot{v}$ are indicated in Figure 12.

The comparison between the mechanical controller and the predictive controller

In order to make clearly the differences between the mechanical controller (introduced in the introduction section) affected by the stiction phenomenon and the predictive controller eliminating the stiction phenomenon, we make a comparison of the results of the valve positioning control as shown in Figure 13.

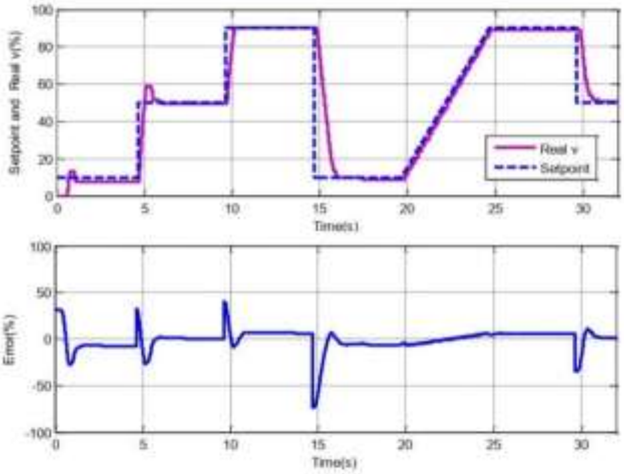

Figure 11. The result of the valve position using the predictive controller with the state observer Kalman

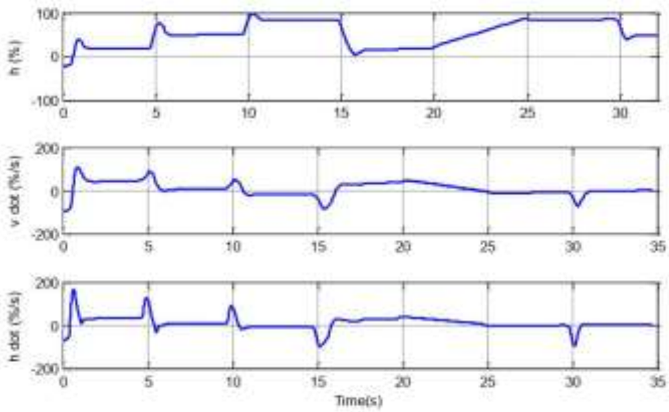

Figure 12. The changes of h, $\dot{h}$, and $\dot{v}$

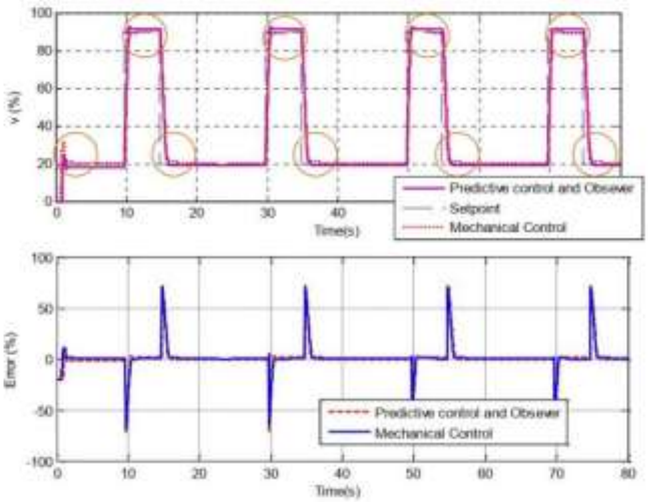

Figure 13. The results when applying the mechanical and predictive controllers

From the comparision it can be sent that the electronics controller designed from the state observer and the predictive controller gives better results than that of the mechanical controller, especially in case of the fast opening/closing statements, or large amplitude. The improvements that the proposed controller brings to the control performance respect to the mechanical control are listed bellow:

- The proposed method may eliminate the stiction phenomena, and make sure that the actual valve position to track the desired trajectory, see the circles on the Figure 13.
- Control errors seem to be almost equal on the beginning time, but the predictive model is usually updated by the time, so the acurracy of the stick model gradualy increases, and the performance of valve position control get better.
- The acurracy of valve position control is better, espescialy for valves which usually perform in the fast openning.

CONCLUSION

The paper proposes the control algorithm for the valve position controlling using the predictive controller and state observer with the non-linear model of the plant. The dynamic phenomenas such as the stiction, sliding delay making the actual valve opening level does not fit to the nominal valve opening level decided by the dynamics of the valve. The stiction dynamic is replaced by higher order transfer function; the piecewisely linearizing model is determined in each sampling cycle, and the Kalman filter is used for determining the states of the valve thereby the predictive controller is applied in each sampling cycle. The predictive window is slided respect to the time axis. Each sliding time is one sampling cycle, and the static linear dynamic is determined again. The optimal control signal for controlling the valve position is also determined in each sampling cycle. The experiment results indicate that the proposed control algorithm works well, and the delay phenomenon caused by the stiction is reduced. The actual valve position tracks to the desired trajectory thereby the controller of the mechanical valve might be replaced by the electronic valve that results of the low cost for the product. Especially, the proposed method can be applicable on the low-tech valves which do not accompany a position controller inside.

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