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ISSN 1812-5638

# INFORMATION TECHNOLOGY JOURNAL

ANSInet
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308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (18): 4790-4796, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.4790.4796


# Stiction Characteristics Identification of Pneumatic Control Valve

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**Abstract:** The stiction characteristic of pneumatic control valve usually leads to the appearance of oscillation phenomena and deteriorates the closed-loop system performance. Thus, modeling the valve stiction is necessary. This study proposes a new system model based on the two-parameter stiction model and the Hammerstein model and exploits the Particle Swarm Optimization (PSO) to estimate the two parameters of the stiction model. At last, simulation and experimental examples verify the effectiveness of the proposed method

**Key words:** Pneumatic control valve, Stiction, Parameter identification

## INTRODUCTION

The nonlinearities of control valve, especially the stiction, are the main reasons of oscillation in closed-loop control system (Jelali and Huang, 2010). The oscillation phenomenon deteriorates deteriorate the loop control performance, leading to product quality reduction, increase of energy consumption rate and accelerating equipment wear. According to literature (Shoukat Choudhury *et al*., 2005), nearly 30% of oscillation phenomenon in closed -loop control system is caused by stiction of regulating valve, so it is necessary to accurately measure the stiction characteristic of control valve in order to eliminate the adverse effects. The literature (Srinivasan *et al*., 2005) proposes a single parameter identification method of stiction characteristic, but the shortcoming is that the single parameter stiction model can not accurately describe the actual stiction properties of pneumatic control valve. The literatures (Shoukat Choudhury *et al*., 2008; Jelali, 2008) are both based on the ellipse fitting method with the difference that their parameter optimal scopes and searching methods are different, but this kind of method is susceptible to the influence of the controller and the process object. To sum up, there is no effective method at present to identify stiction model parameters. Based on the Hammerstein model identification, a new method is proposed to identify the two parameters of the stiction model.

## VALVE STICTION

The literature Shoukat Choudhury *et al*. (2005) gives the definition of regulator stiction properties: Under the action of the input signal, there will be a jump phenomenon before the regulator reaches the smooth movement and the jump dimension is measured in the forms of percentage of the output range. The reason of this phenomenon is that the valve's static friction force is greater than the largest dynamic friction caused by the smooth movement

The models of valve stiction can be divided into three categories, namely the physical model, the single parameter model and two parameters model. The single parameter model and two parameters model are data driven models. The defect of physical model is that there is more than one unknown parameter which is hard to identify and brings great difficulty in practical operation. The single single parameter model can not accurately describe the actual characteristics of regulator.

In order to better describe the sticiton properties of regulator, Shoukat Choudhury *et al.* (2005), Kano *et al.* (2004), He *et al.* (2007) and Chen *et al.* (2008), put forward their individual data driven models which are based on double parameters S and J, where S represents the dead-zone plus stiction parameter and J represents the temporary jump parameter. Since S-J model proposed by Choudury can only deal with deterministic input signal, Kano puts forward a model which can handle both determined signal and random signal. But it cannot describe the several states of valve stiction directly. He *et al.* (2007) proposed a simplified double parameters model. This model is based on the sliding friction force $f_s$ and the maximum static friction force $f_d$. The relationship between S, J and $f_s$, $f_d$ of the regulator is as follows:

$$\begin{cases} S = f_s + f_d \\ J = f_s - f_d \end{cases} \quad (1)$$

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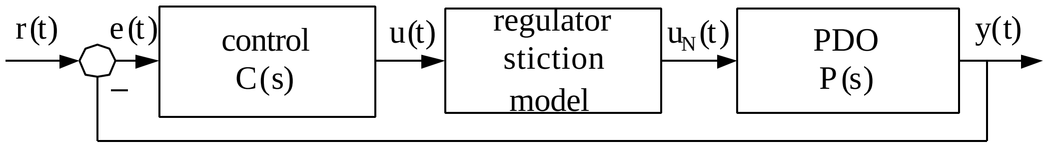


Fig. 1: Closed-loop control of regulator stiction model

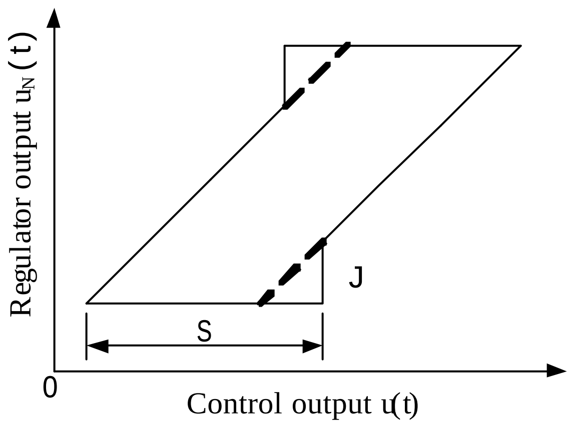


Fig. 2: Control output and regulator output

Chen points out that He's model can only deal with two kinds of states among the whole four kinds, namely keeping the stiction state and the transforming from sticiton to sliding state. Based on He's model, Chen adds another two states which are transforming from sliding to stiction status and keeping sliding respectively which make the model more effective. The specific flow chart of the model can be seen in literature (Chen *et al.*, 2008).

The block diagram of closed loop control system with valve stiction is shown as Fig. 1. (PDO: Process data objects ), where r (t), e (t), u (t), $u_N$ (t), y (t) are shown as the input, tracking error, the controller output, regulator output and system output respectively. The relationship between the controller output and regulator output is shown as Fig. 2.

## STICTION PARAMETERS IDENTIFICATION

In the stiction parameter identification, usually the input r (t), controller output value u (t) and process output value y (t) are accessible. For the convenience of calculation, assume that the control object is a linear process and the stiction characteristic of control valve can be described by Chen's double parameters data driven model. Through the calculation of minimum mean square error between predicted output $\hat{y}(t)$ and the actual

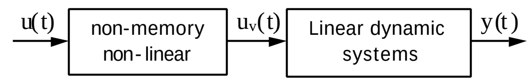


Fig. 3: Hammerstein model

output y(t), corresponding optimal estimated value can be achieved. So, the stiction parameters identification problem can be transformed into the optimal problem of calculating mean square error:

$$\left(\hat{S},\hat{J}\right) = \arg\min\left(\sum_{i=1}^{N}(y(t)-\hat{y}(t))^2\right) \tag{2}$$

$$\hat{y}(t) = G_p(u_N'(t))$$

$$u_N'(t) = N_{stic}(u(t),\hat{S},\hat{J})$$

where, $(\hat{S},\hat{J})$ are the estimated values of stiction parameters. u (t), y (t) is the output value of controller and the process output value respectively, $u_N$' (t) is the corresponding output of control valve model, $N_{stic}$ is the nonlinear model of regulator with stiction and $G_p$ is the transfer function of process object

**Hammerstein model introduction:** The nonlinear system described by Hammerstein's model consists of a non-memory nonlinear block and a dynamic linear block in series form which is shown in Fig. 3.

Where, u (t), $u_v$ (t) and y (t) represent the input, the internal input and output of the Hammerstein model respectively. The immeasurable signal h the output of the nonlinear part and the input of the linear part. The Linear dynamic part of Hammerstein model is described by a linear discrete transfer function G $(q^{-1})$ with where $(q^{-1})$ represents backward shift operator.

The nonlinear part of Hammerstein model is usually described by a polynomial as follows:

$$u_v(t) = \gamma_1 u(t) + \cdots + \gamma_k u^k(t) = \sum_{i=1}^{k}\gamma_i u^i(t) \tag{3}$$

The linear part of Hammerstein model can be shown by using ARMAX model as follows:

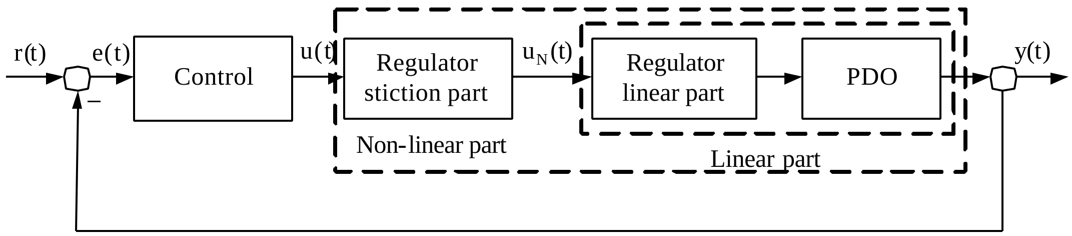


Fig. 4: Process-control loop

$$A(q^{-1})y(t) = B(q^{-1})u_v(t) + C(q^{-1})\xi(t) \quad (4)$$

where $\xi(t)$ is the noise; A $(q^{-1})$, B $(q^{-1})$ and C $(q^{-1})$ are polynomial functions of $q^{-1}$ with coefficients $a_i$, $b_i$, $c_i$ respectively, i.e., $q^{-1}$; $a_i$, $b_i$, $c_i$ are equation coefficients:

$$\begin{cases} A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_n q^{-n} \\ B(q^{-1}) = b_1 q^{-1} + b_2 q^{-2} + \cdots + b_m q^{-m} \\ C(q^{-1}) = 1 + c_1 q^{-1} + c_2 q^{-2} + \cdots + c_p q^{-p} \end{cases}$$

The optimal prediction of parameters can be got by the following equation:

$$A(q^{-1})\hat{y}(t,\Theta) = B(q^{-1})\sum_{i=1}^{k} \gamma_i u^i(t) + \xi(t) \quad (5)$$

Thus the unknown parameters of Hammerstein model can be estimated by minimizing the minimum mean square error of the following equation:

$$V(\Theta) = \frac{1}{N}\sum_{t=1}^{N} (y(t) - \hat{y}(t))^2 \quad (6)$$

**Improvement of parameter identification mode:** The valve stiction property is not only discontinuous, but also nonlinear and has memory. Thus, the stiction model needs to be different from common Hammerstein model.

In order to identity the parameters of valve stiction characteristic, use the double parameters model proposed by Chen *et al*. (2008) as the nonlinear part of Hammerstein model and form a new model. In order to the unknown parameters of the new model, a new model diagram is built as in Fig. 4:

For the convenience of identification, assume that the linear part is described by the ARX model:

$$A(q^{-1})y(k) = q^{-\tau}B(q^{-1})u_v(k) + \xi(k) \quad (7)$$

where, $A(q^{-1})$ and $B(q^{-1})$ is the same as Eq. 4, $\tau$ is the time delay of the process object.

Stiction nonlinearity can be written as the universal expression:

$$u_v(k) = NL_{stic}\left(u(k), \cdots, u(0), u_v(k-1), \cdots, u_v(0), S, J\right) \quad (8)$$

S and J are set as constants. Note that the internal signal $u_v(k)$ can not be measured.

Assume that both A $(q^{-1})$ and B $(q^{-1})$ are of order n, the output can be written as follows:

$$y(k) = \Theta^T[y(k-1), \cdots, y(k-n), u_v(k-\tau-1), \cdots, u_v(k-\tau-n)] + \xi(k) \quad (9)$$

$$\Theta = [-a_1, \cdots, -a_n, b_1, \cdots, b_n]^T$$

According to the estimated values of stiction properties, the valve position signal, i.e., $u_N(t)$ can be estimated as $\hat{u}_v(k)$ by the following equation:

$$\hat{u}_v(k) = NL_{stic}\left(u(k), \cdots, u(0), \hat{u}_v(k-1), \cdots, \hat{u}_v(0), \hat{S}, \hat{J}\right) \quad (10)$$

where, u(k) is not only the output of the controller but also the input signal of the regulator; $\hat{u}_v(k)$ is the estimation of valve position signal.

The prediction error between the actual output and estimated output is:

$$\begin{aligned} \varepsilon_{\hat{\theta},\hat{J},\hat{S}}(k) &= y(k) - \hat{y}(k) \\ &= y(k) - \hat{\Theta}^T[y(k-1), \cdots, y(k-n), \\ &u_v(k-\tau-1), \cdots, u_v(k-\tau-n)] \quad k = 1, 2 \cdots N \end{aligned} \quad (11)$$

where, $\hat{y}(k)$ is the estimation of the system output and $\hat{\Theta}$ is the $\hat{\Theta}$ estimated parameters of the process object.

The objective function which is Mean Square Error (MSE) may be defined as:

$$V(\hat{S}, \hat{J}, \hat{\Theta}) = \frac{1}{N}\sum_{k=1}^{N} \varepsilon^2_{\hat{S},\hat{J},\hat{\Theta}}(k) \quad (12)$$

where, N represents the number of sampling points. To solve the stiction parameters of regulator is equivalent to solving the minimum problem of the objective function:

$$\left[\hat{S}, \hat{J}, \hat{\Theta}\right] = \arg\min V_N\left(\hat{S}, \hat{J}, \hat{\Theta}\right) \quad (13)$$

In actual industry application, the parameters of the process object are usually unknown, meaning the parameters\theta needs to be estimated. So, it is difficult to solve the minimum mean square problem directly by Eq. 12, to get the optimal solution of S and J.

For the convenience of solution, let:

$$y = \begin{bmatrix} y(n+\tau) \\ y(n+\tau+1) \\ \vdots \\ y(N) \end{bmatrix} \quad (14)$$

$$\Phi(\hat{S}, \hat{J}) = \begin{bmatrix} y(n+\tau+1) & \cdots & y(\tau) & \hat{u}_v(n-1) & \cdots & \hat{u}_v(0) \\ y(n+\tau) & \cdots & y(\tau+1) & \hat{u}_v(n) & \cdots & \hat{u}_v(1) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y(N-1) & \cdots & y(N-n) & \hat{u}_v(N-\tau-1) & \cdots & \hat{u}_v(N-n-\tau) \end{bmatrix} \quad (15)$$

With this Eq. 12 can be written as:

$$V_N = \frac{1}{N}\left\| y - \Phi(\hat{S}, \hat{J})\hat{\Theta} \right\|_2 \quad (16)$$

Calculating the derivative of V_N on \theta, we get:

$$0 = \frac{1}{2}\frac{\partial V_N}{\partial \hat{\Theta}} = -\Phi(\hat{S}, \hat{J})y + \Phi^T(\hat{S}, \hat{J})\Phi(\hat{S}, \hat{J})\hat{\Theta} \quad (17)$$

When $\Phi^T(\hat{S}, \hat{J})\Phi(\hat{S}, \hat{J})$ is reversible, the process model parameter can be estimated as:

$$\hat{\Theta} = \left[\Phi^T(\hat{S}, \hat{J})\Phi(\hat{S}, \hat{J})\right]^{-1} \Phi^T(\hat{S}, \hat{J})y \quad (18)$$

Substituting Eq. 18 into 12 yields:

$$V_N = \frac{1}{N}\left\| y - \Phi(\hat{S}, \hat{J})\left[\Phi^T(\hat{S}, \hat{J})\Phi(\hat{S}, \hat{J})\right]^{-1} \Phi^T(\hat{S}, \hat{J})y \right\|_2 \quad (19)$$

With Eq. 13 and 19 the stiction characteristic parameter S and J can be estimated.

**Confirm the range of parameters optimization:** To calculate the optimal solution of the Eq. 12, the search ranges of optimal parameters need to be determined.

For the stiction properties of regulating valve, the parameter S is usually larger than parameter J. So, once the value range of S is determined, it is easy to get the value range of J.

The estimated value of oscillation period of the loop can be achieved through the deviation e (t) = r (t)-y (t) between the set value r (t) and process output value e (t):

$$T = \max(\Delta T_k) = \max(T_{k+1} - T_k) \quad k = 1, 2, \cdots, M \quad (20)$$

where, $T_{k+1}$-$T_k$ is a cycle of loop oscillation; M is the time of sampling.

By the controller output u(t) and its figure, we can observe the oscillation amplitude range of u(t) in each cycle. Taking the maximum oscillation amplitude range as the search range of S, we have:

$$S_{max} = \max(u(t)) - \min(u(t)) \quad t \in [T_k, T_{k+1}] \quad (21)$$

When the range of stiction parameter search range is determined, the particle swarm optimization algorithm is applied to determine the estimations of stiction parameters.

## SIMULATION AND EXPERIMENTAL ANALYSIS

In order to validate the effectiveness, of the proposed identification method both matlab simulation and experimental examples are presented

**Simulation analysis:** On the Matlab/Simulink platform, the closed-loop simulation system is built as shown in Fig. 5. In the chart, the Process model is linear and its parameters are set according to actual needs. The Stiction Subsystem is the valve stiction model, whose internal connection can be shown in Fig. 6.

In the simulation, the system input r(t) is given as a step signal whose amplitude is 5% of the valve position range. The sampling data length is 1000 and the sampling interval is 1 s. The process objects are respectively set as First Order Plus Time Delay (FOPTD) and Integral Time Plus Time Delay (ITPTD) systems. Their parameters and corresponding controller are shown in Table 1.

To illustrate the validity of the identification method, different groups of ($S_i$, $J_i$) are simulated and the results

Table 1: Parameters of the process object and controller

| PDO | Process model | Control model |
|---|---|---|
| FOPTD | $G_p = \frac{3}{5s+1}e^{-5s}$ | $G_c = 0.1(1+\frac{1}{5s})$ |
| ITPTD | $G_p = \frac{1}{s(0.3s+1)}e^{-s}$ | $G_c = 0.1(1+\frac{1}{5s})$ |

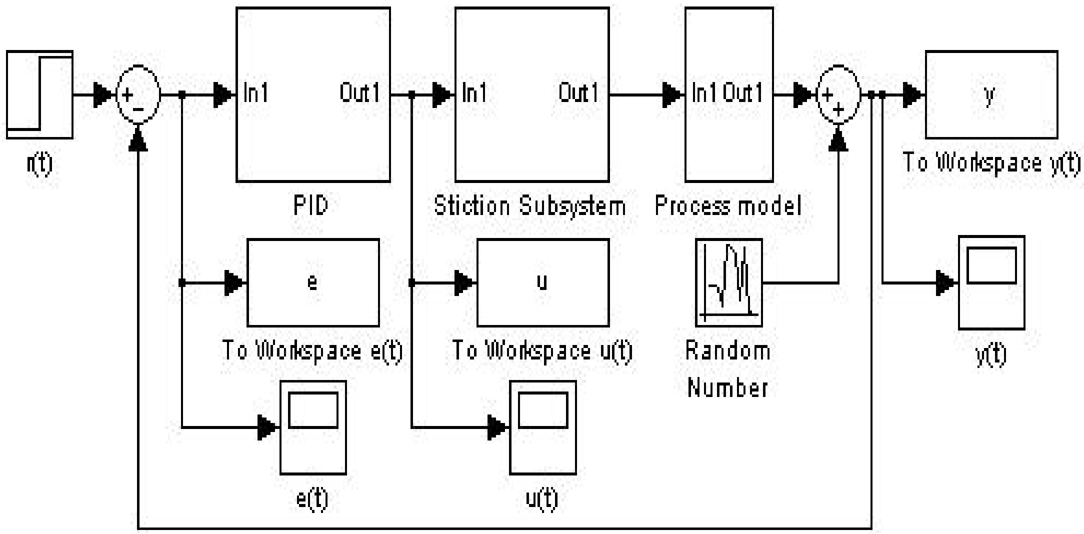


Fig. 5: Regulator stiction identification simulation

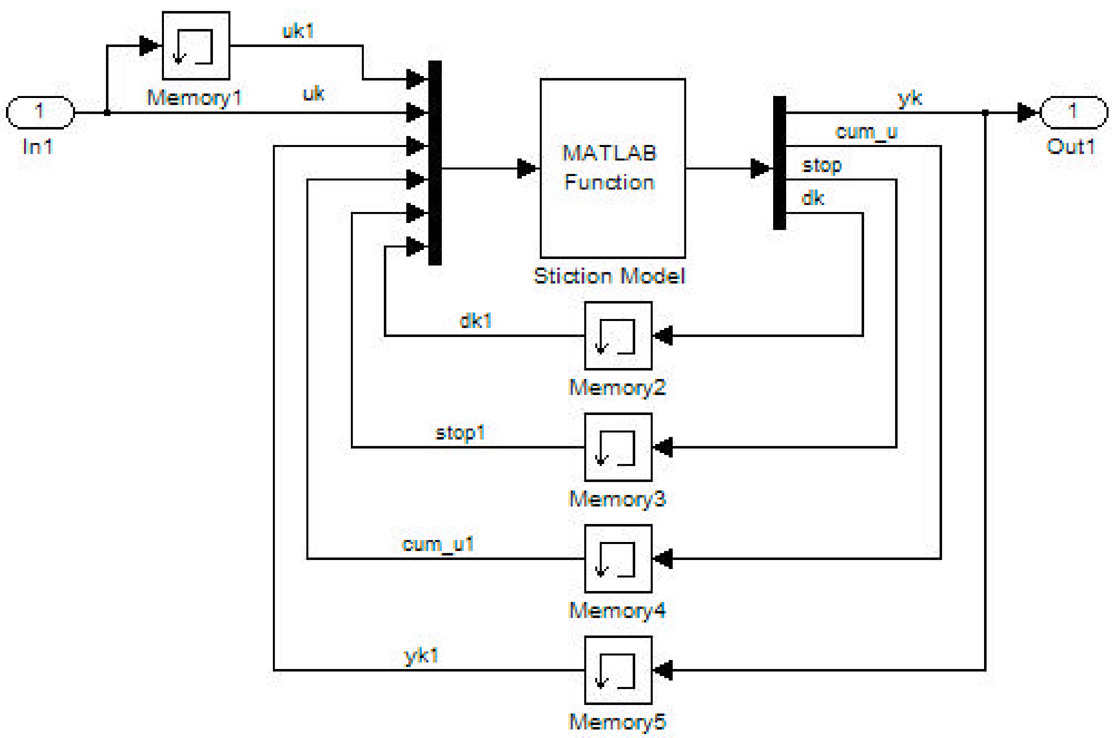


Fig. 6: Regulator stiction subsystem simulation

of identification are shown in chart 2 and 3 where $e_S$% and $e_J$% are the errors of S and J in terms of percentage.

**Experimental analysis:** To validate the effectiveness of the identification method proposed in this study, Liquid level control experiments are carried out on the platform ofJX-300XP distributed control system produced by XX Co., LTD and AE2000 experimental equipment, including the SF10TD- (10)1200C11-1.2 m/h electromagnetic flow meter, JHHLS-16K-20pneumatic control valve and the

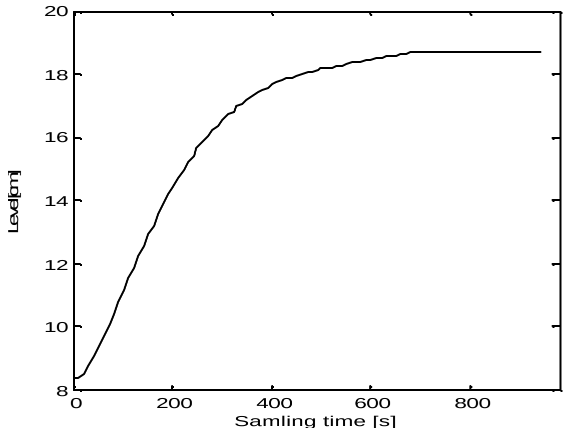


Fig. 7: Liquid level open loop step input response curves

Table 2: Identification result of FOPTD system

| Actual stiction parameters (%) | | Estiamte stiction parameters (%) | | Optimal range (%) | Percentage error | |
|---|---|---|---|---|---|---|
| S | J | $\hat{S}$ | $\hat{J}$ | $S_{max}$ | $e_S$(%) | $e_J$(%) |
| 3.5 | 3.5 | 3.452 | 3.471 | 4.118 | 1.370 | 0.830 |
| 4.0 | 3.5 | 3.931 | 3.542 | 4.582 | 1.725 | 1.200 |
| 4.5 | 3.5 | 4.484 | 3.484 | 5.065 | 0.350 | 0.450 |
| 5.0 | 1.5 | 4.981 | 1.487 | 5.235 | 0.380 | 0.867 |
| 5.0 | 3.5 | 4.974 | 3.513 | 5.583 | 0.530 | 0.370 |
| 5.0 | 2.0 | 4.985 | 1.992 | 5.336 | 0.300 | 0.400 |
| 5.0 | 3.0 | 4.987 | 3.016 | 5.591 | 0.260 | 0.533 |
| 5.0 | 4.0 | 4.975 | 3.969 | 5.687 | 0.500 | 0.775 |

Table 3: Identification result of ITPTD system

| Actual stiction parameters (%) | | Estiamte stiction parameters (%) | | Optimal range (%) | Percentage error | |
|---|---|---|---|---|---|---|
| S | J | $\hat{S}$ | $\hat{J}$ | $S_{max}$ | $e_S$(%) | $e_J$(%) |
| 3.5 | 3.5 | 3.432 | 3.468 | 4.902 | 1.94 | 0.91 |
| 4.0 | 3.5 | 3.913 | 3.512 | 5.737 | 2.18 | 0.34 |
| 4.5 | 3.5 | 4.452 | 3.487 | 6.598 | 1.07 | 0.37 |
| 5.0 | 1.5 | 4.896 | 1.483 | 9.659 | 2.08 | 1.13 |
| 5.0 | 3.5 | 4.917 | 3.486 | 7.486 | 1.66 | 0.40 |
| 5.0 | 2.0 | 4.912 | 1.955 | 8.848 | 1.76 | 2.25 |
| 5.0 | 3.0 | 4.889 | 3.104 | 7.829 | 2.22 | 3.47 |
| 5.0 | 4.0 | 4.904 | 3.879 | 7.238 | 1.92 | 3.03 |

VEP-300 smart positioner. The upper tank (20*38cm) and the lower tank (24×30 cm) form the double-tank system and the system is controlled by the configuration software.

Before the closed-loop experiment, we have to measure the characteristic of the tank and tune the PID controller parameters. When calculating the stiction parameters, the delay time of the process objective needs to be determined. The time delay\tau is approximated by the measurement of the double-tank system in the open-loop form.The liquid levels change with time shown in Fig. 7.

It turns out that the process objective can be described by a FOPTD:

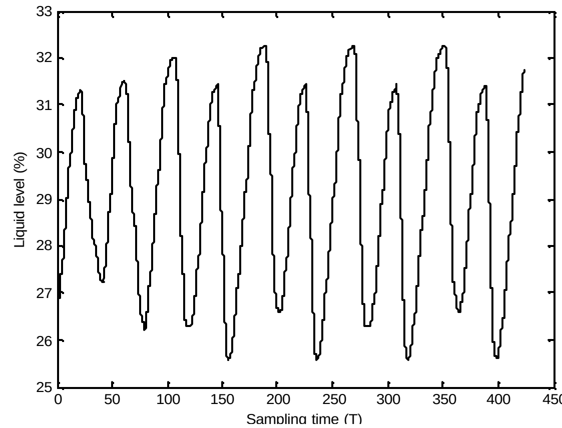


Fig. 8: Liquid level measured curve

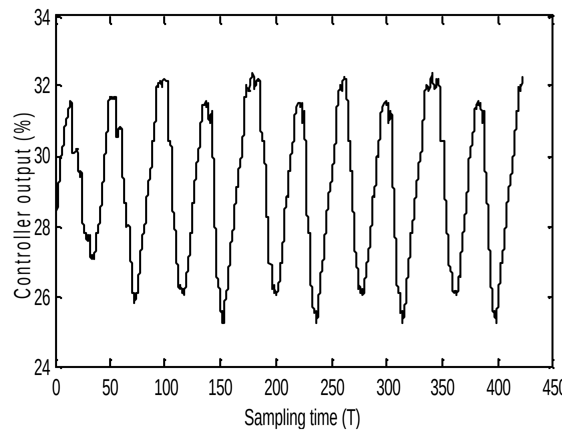


Fig. 9: Controller measured curve

$$G(s)=\frac{2.286}{180s+1}e^{-36.67s} \quad (21)$$

Collect the data of liquid level and normalize it into percentages of liquid level range. The oscillation curve is shown in Fig. 8.

Collect the controller output u(t) so that we can determine the stiction parameters search range. The change curve of controller can be drawn as in Fig. 9. By which the search range of stiction parameter is set as (0~11.34%).

With the data {u(t), y(t)} the PSO (Sreenivasan, 2011; Yu and Lichen, 2013) estimates the stiction parameters as:

$$\hat{S}=1.746\%,\ \hat{J}=1.325\%$$

Based on the controller output signal u(t) and the valve position u_N(t) measured by the smart positioner, the input and output characteristic curves of the regulator

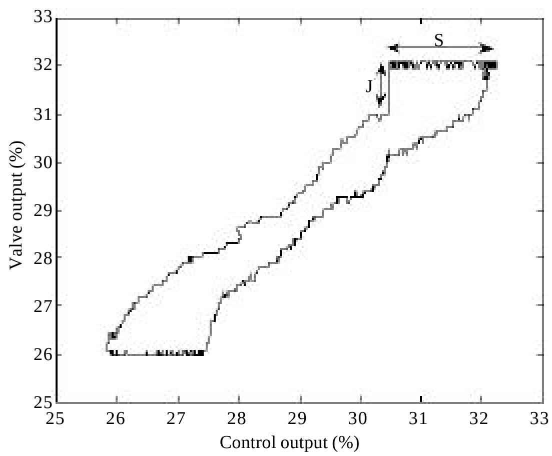


Fig. 10: Regulator output

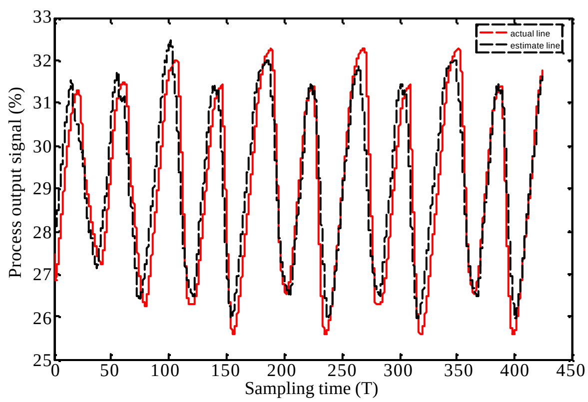


Fig. 11: Actual level output and estimated level output

in control circuit can be drawn, as shown in Fig. 10.From the chart we can see sticiton parameter S is close to 1.678% and parameters J is close to 1.159%. So, the stiction parameter identifications are close to the real values.

In order to make further explanation to the validity and accuracy of the stiction parameter identification algorithm, by adding actual controller output signal and double parameters stiction model with estimated S and J to the measured process objective model, simulation is done on the platform of Matlab to get the predicted output. The comparison between the model prediction and the measured data is shown in Fig. 11.

In the Fig. 11, estimated output curve and the actual measured level curve are much closed, proving that the proposed identification algorithm is effective. But it also shows that there is unavoidable disturbance and the data errors, so certain deviations between estimated output signals and real output signals.Exists This deserves a further study.

## CONCLUSION

This study proposed a new identification method of regulator stiction parameters which was based on a Hamerstein model with the two-parameter stiction model as the nonlinearity. The stiction parameters were estimated by the PSO and could accurately predict the liquid level. The effectiveness of the proposed method was verified by simulation and experimental examples.

## ACKNOEELEDGMENT

The authors would like to acknowledge for assistance of National Natural Science Foundation of China under Grants No 61174108.

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