A Single Curve Piecewise Fitting Method for Detecting Valve Stiction and Quantification in Oscillating Control Loops

S. Kalaivani, T. Aravind and D. Yuvaraj

Abstract Stiction is one of the most common problems in the spring-diaphragm type control valves, which are widely used in the process industry. In this paper, a procedure for single curve piecewise fitting stiction detection method and quantifying valve stiction in control loops based on ant colony optimization has been proposed. The single curve piecewise fitting method of detecting valve stiction is based on the qualitative analysis of the control signals. The basic idea of this method is to fit two different functions, triangular wave and sinusoidal wave, to the controller output data. The calculation of stiction index (SI) is introduced based on the proposed method to facilitate the automatic detection of stiction. A better fit to a triangular wave indicates valve stiction, while a better fit to a sinusoidal wave indicates non-stiction. This method is time saving and easiest method for detecting the stiction. Ant colony optimization (ACO), an intelligent swarm algorithm, proves effective in various fields. The ACO algorithm is inspired from the natural trail following behaviour of ants. The parameters of the Stenman model estimated using ant colony optimization, from the input–output data by minimizing the error between the actual stiction model output and the simulated stiction model output. Using ant colony optimization, Stenman model with known nonlinear structure and unknown parameters can be estimated.

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1 Introduction

Large-scale, highly integrated processing plants include some hundreds or even thousands of control loops. The aim of each control loop is to maintain the process at the desired operating conditions, safely and efficiently. A poorly performing control loop can result in disrupted process operation, degraded product quality, higher material or energy consumption and thus decreased plant profitability.

Nonlinearities such as stiction, backlash and dead band cause oscillations in the process output. They may be present in the process itself or in the control valves. Among the many types of nonlinearities in control valves, stiction is the most common problem in the control valves, which are widely used in the process industry. It hinders the proper movement of the valve stem and consequently affects control loop performance. As the presence of oscillation in a control-loop increases the variability of the process variables, thus causing inferior quality products and larger rejection rates, it is important to detect and quantify stiction. The single curve piecewise fitting method involves fitting the single curve of OP to both triangular and sinusoidal waves using least square estimation (LSE). A better fit to a triangular wave indicates valve stiction, while a better fit to a sinusoidal wave indicates nonstiction. This method is time saving and easiest method for detect the stiction. All valves are sticky to some extent, it is important to quantify stiction. The quantification is implemented by an ant colony optimization procedure. The ant colony optimization procedure involves certain steps to estimate the parameter values. The parameter estimation is done by minimizing the objective function. The error (e) is the difference between actual stiction model output (y) and the dynamic stiction model output (y_m). It is used as the criterion to correct the model parameters, so as to identify the parameters of the actual process.

2 Valve Stiction Model

The present work focuses on pneumatic control valves, which are widely used in the process industry. The general structure of pneumatic control valve is shown in Fig. 1.

Stiction is a portmanteau word formed from the two words static friction. Stiction is the static friction that prevents an object from moving and when the external force overcomes the static friction the object starts moving [1]. The presence of stiction impairs proper valve movement, i.e. the valve stem may not move in response to the output signal from the controller or the valve positioner. To check the behaviour

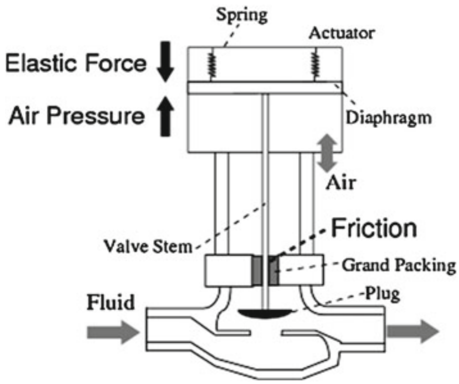

Fig. 1 Structure of pneumatic control valve

of valve moment by modelling, the stiction detection made by physical model and Stenman model used to quantification process.

2.1 Physical Model of Valve Friction

The purpose of this section is to understand the physics of valve friction and reproduce the behaviour seen in real plant data. For a pneumatic sliding stem valve, the force balance equation based on Newton's second law can be written as,

$$M\frac{d2x}{dt2} = \sum Force = Fa + Fr + Ff + Fp + Fi \quad (1)$$

where,

M = Mass of the moving parts, x = Relative stem position.
$F_a = Au$ = Force applied by pneumatic actuator (A = Area of the diaphragm, u = Actuator air pressure or the valve input signal).
$F_r = -kx$ = Spring force (k = Spring constant).
$F_p = -\alpha \Delta P$ = Force due to fluid pressure drop (α = plug unbalance area, ΔP = Fluid pressure drop across the valve).
F_i = Extra force required to force the valve to be into the seat.
F_f = Friction force includes static and moving friction.

where

$$F_f = \begin{cases} F(v) & \text{if } v \neq 0 \\ -(F_a + F_r) & \text{if } v = 0 \text{ and } |F_a + F_r| \leq F_s \\ -\text{Fs sign } (F_a + F_r) & \text{if } v = 0 \text{ and } |F_a + F_r| > F_s \end{cases} \quad (2)$$

Table 1 Values of F_s and F_c for different levels of stiction

Magnitude of stiction	F_s(lbf)	F_c (lbf)
Weak stiction	384	320
Strong stiction	600	500

$$F(v) = -F_c sgn(v) - vF_v - (F_s - F_c) \exp(-v/vs) 2 sgn(v) \tag{3}$$

The expression for the moving friction is in the first line of equation and comprises a velocity independent term F_c known as Coulomb friction and a viscous friction term vF_v that depends linearly upon velocity. Both act in opposition to the velocity, as shown by the negative signs.

The second line in equation is the case when the valve is stuck. F_s is the maximum static friction. The velocity of the stuck valve is zero and not changing; therefore, the acceleration is zero also. Thus, the right-hand side of Newton's law is zero, so $F_f = -(F_a + F_r)$.

The third line of the model represents the situation at the instant of breakaway. At that instant, the sum of forces is $(F_a + F_r) - F_s sgn(F_a + F_r)$, which is not zero if $|F_a + F_r| > F_s$. Therefore, the acceleration becomes nonzero and the valve starts to move. Here, F_i and F_p assumed to be zero because of their negligible contribution in the model Table 1.

3 Proposed Single Curve Piecewise Fitting Detection Method

Single curve piecewise fitting method of detecting valve stiction is based on the qualitative analysis of the control signals [2]. The basic idea of this method is to fit two different functions, triangular wave and sinusoidal wave, to the controller output (OP) data. The response of physical model is considered as the valve stiction, the stiction detection method is based on the single curve piecewise fitting results of the output signal of first integrating processes, and finally, according the calculation of stiction index, it is introduced based on the proposed method to facilitate the automatic detection of stiction [3].

3.1 Method Description

The single curve piecewise fitting based identification algorithm can be summarized in the following steps:

Step 1: Simulated the closed-loop stiction model in pneumatic control valves.
Step 2: M output data points are generated from the system to be identified [4].

Step 3: In the case of stiction-induced oscillations, the valve position switches back and forth periodically, which results in a rectangular wave.

Step 4: The first integrator after the valve in the control loop converts it into a triangular wave.

Step 5: A sinusoidal external disturbance results in sinusoidal controller output (OP) and process variable (PV), as the integration of a sine wave results in a sinusoidal wave with phase shift.

Step 6: A marginally stable control loop also results in smooth sinusoidal-shaped controller output (OP) and process variable (PV) for the same reason as for a sinusoidal external disturbance.

Step 7: Random initial values for parameters of the nonlinearities in the appropriate range are generated. Choose the any single curve from the controller output [5].

Step 8: Generate the single sine wave and triangular wave and fit with controller output, the objective function for each particle in the initial population is evaluated.

Step 9: Judge end of the iteration and output the best solution, while a better fit to a sinusoidal wave indicates nonstiction. A better fit to a triangular wave indicates valve stiction.

Step 10: According to the stiction index, value used to find the magnitude of stiction.

3.2 Stiction Index

The stiction index (SI) is defined as the ratio of the MSE of the sinusoidal fit to the summation of the MSEs of both sinusoidal and triangular fits: SI is bounded to the interval [0, 1]. The mathematical expression for SI can be written as

$$\mathrm{SI} = \frac{\mathrm{MSEsin}}{\mathrm{MSEsin} + \mathrm{MSEtri}} \tag{4}$$

$\mathrm{SI} = 0$ indicates nonstiction, where S(t) fits a sinusoidal wave perfectly ($\mathrm{MSEsin} = 0$), $\mathrm{SI} = 1$ indicates stiction, where S(t) fits a triangular wave perfectly ($\mathrm{MSEtri} = 0$). For real process data, an SI close to 0 would indicate nonstiction, while an SI close to 1 would indicate stiction. SI is around 0.5, which means MSEsin = MSEtri, and it is undetermined.

Based on the experience, the following rules are recommended:

$$\begin{aligned} &\mathrm{SI} \le 0.4 = \text{ no stiction} \\ &0.4 < \mathrm{SI} < 0.6 = \text{undetermined} \\ &\mathrm{SI} \ge 0.6 = \text{stiction} \end{aligned} \tag{5}$$

4 Data-Driven Stiction Model

Stenman et al.[1] with reference to a private communication with Hagglund reported a one-parameter data-driven stiction model. Stenman proposed a single-parameter data-driven stiction model based on d. Since physical model has certain disadvantages, a single-parameter data-driven model is used for quantifying stiction.

The model is described as follows:

$$x(t) = \begin{cases} x(t-1) & \text{if } |u(t) - x(t-1) \leq d| \\ u(t) & \text{otherwise} \end{cases} \tag{6}$$

where u and x are the valve input and output, $x(t-1)$ and $x(t)$ represent past and present stem positions, $u(t)$ is the actual controller output, and d is the valve stiction band. The model compares the difference between the current input $(u(t))$ to the valve and the previous output $(x(t-1))$ of the valve with the dead band. A real valve can stick anywhere whenever the input reverses direction.

5 Ant Colony Optimization

Ant colony algorithm was first introduced by E. Bonabeau and M. Dorigo in 1991, and the algorithm is a simulation-based evolution process of the real ant seeking food. In 1992, ant colony optimization (ACO) takes inspiration from the foraging behaviour of some ant species. A foraging ant deposits a chemical (pheromone) on the ground which increases the probability that the other ant will follow the same path. This type of communication is also known as stigmergy [6].

The basic procedure of ACO involves certain steps to estimate the unknown parameters of the system. The flowchart of the basic ant colony optimization is shown in Fig. 2.

The main principle of ACO is to minimize the objective function which is also represented as fitness function. If this objective function does not reach the minimum value, the next iteration starts by updating the pheromones. The pheromone is updated till the objective function reaches the minimum value [7].

6 Principle and Implement of Parameter Estimation Using ACO

The framework of ACO-based parameter estimation of the Stenman stiction model is illustrated in Fig. 3. The quantification of process nonlinearity can help decide whether to implement a nonlinear controller or not. It is important to measure the degree of nonlinearity of a process under various input excitation signals or operating

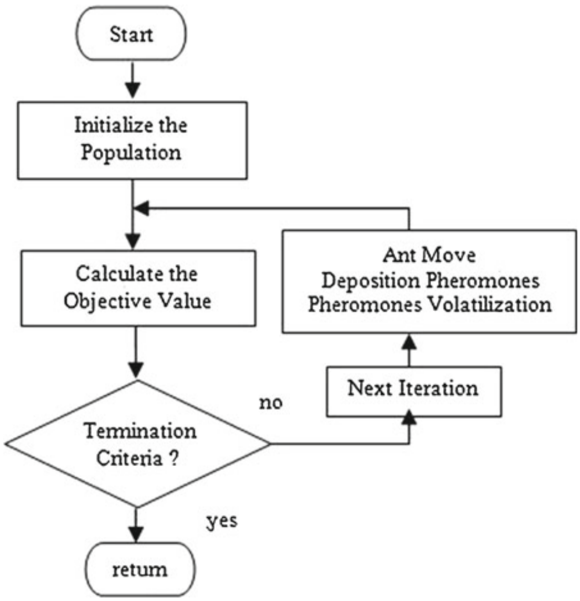

Fig. 2 Flowchart of the basic ant colony optimization

conditions [6]. The quantification is implemented by an ant colony optimization procedure. The open-loop response is obtained for Stenman stiction model.

Since, Stenman model is a single-parameter model, the valve stiction band (d) is to be estimated by obtaining the difference between the actual stiction model output $y(t)$ and simulated stiction model output $y_m\ (t)$, $u(t)$ is the system input signal that can be used in common to both the actual stiction model and simulated stiction model

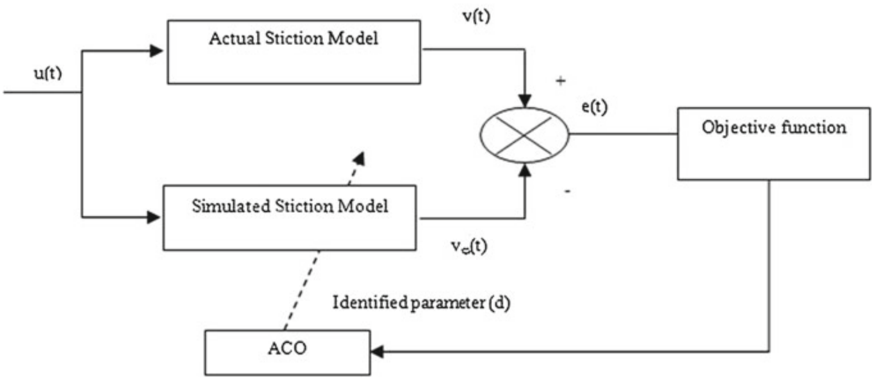

Fig. 3 ACO-based parameter estimation procedure

The following objective function (fitness function) can be defined so as to determine how well the estimates fit the system [8].

$$F = \sum_{t=1}^{M} (y(t) - y_m(t))^2 \quad (7)$$

The ant colony optimization automatically adjusts the parameters of the simulated stiction model. The ACO procedure is used to minimize the objective function which is the difference between the actual stiction model output $y(t)$ and the simulated stiction model output $y_m(t)$.

6.1 Algorithm for Parameter Estimation

6.1.1 Initialize the Pheromone

For constructing a solution, an ant chooses at each construction step $t = 1, \ldots$m, a value for decision variable x_i in m dimensional problem. While termination condition not met, do [10].

```
Procedure ACO
begin
        Initialize the pheromone
        while (stopping criterion not satisfied) do
          Position each ant in a starting point
          while (stopping when every ant has
                    build a solution) do
for each ant do
                    Chose position for next task by
                    pheromone trail intensity
          end for
          end while
update the pheromone
end while
end
```

6.1.2 Ant Solution Construction

The tour length for the kth ant, L_k, the quantity of pheromone added to each edge belonging to the completed tour is given by the following equation

$$\Delta\tau_{ij}^{k}(t) \begin{cases} \frac{Q}{L_k} & \text{where edge } (i, j) \in T_k(t) \\ 0 & \text{if edge } (i, j) \notin T_k(t) \end{cases} \quad (8)$$

where τ_{ij} is the trail intensity which indicates the intensity of the pheromone on the trail segment (ij), and Q represents the pheromone quantity [10].

6.1.3 Pheromone Update

After performing local searching, the pheromone table is updated by using the former ants. The pheromone decay in each edge of a tour is given by

$$\tau_{ij}\,(t+1) = (1-\rho)\,\tau_{ij}\,(t) + \Delta\tau_{ij}\,(t) \tag{9}$$

where $\rho \in (0, 1)$ is the trail persistence or evaporation rate. The greater the value of ρ is, the less the impact of past solution is. When the ant completes its tour, the local pheromone updating is done. The value of $\Delta\tau_j$ is defined as follows:

$$\Delta\tau_j = \frac{1}{T_{ik}} \tag{10}$$

where T_{ik} is the shortest path length that searched by kth ant at ith iteration. When the ant completes its tour, if it finds the current optimal solution, it can lay a larger intensity of the pheromone on its tour, and the global pheromone updating is applied and the value of $\Delta\tau_j$ is given by

$$\Delta\tau_j = \frac{D}{T_{\text{op}}} \tag{11}$$

where T_{op} is the current optimal solution, and D is the encouragement coefficient.

7 Results and Discussion

In this section, several simulations are performed for detecting pneumatic control valve stiction in the closed loop of a physical model using MATLAB/Simulink software. The control valve stiction is detected by obtaining the closed-loop response of valve stiction. To study the effect of stiction, a first-order process with a time-delay was simulated using a pneumatic control valve modelled using Newton's second law.

$$G(s) = \frac{1.54e^{-1.07s}}{5.93s + 1} \tag{12}$$

The model parameters used in the simulation are given below. The values of fs and fc are as per the Table 3.1. $A = 1{,}000\ \text{in}^2$, $k = 300\,\text{lbf.in}^{-1}$, $M = 3\,\text{lb}$, $F_v = 3.5\,\text{lbf.s.in}^{-1}$, vs $= 0.01$. Figures 4a and 4b show the variations of controller output, plant output and valve output in the presence of weak stiction and strong stiction, respectively.

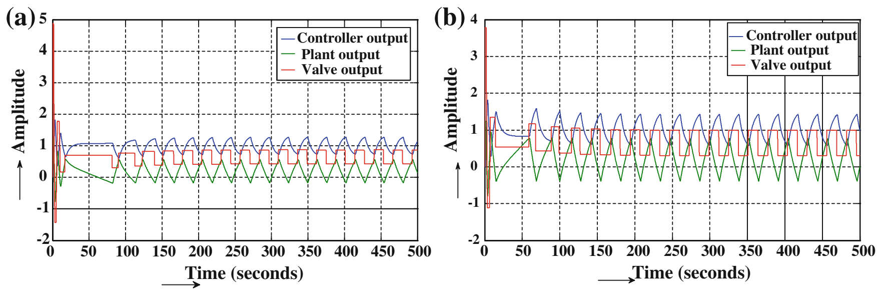

Fig. 4 **a** Closed-loop response of physical model in the case of weak stiction, **b** closed-loop response of physical model in the case of strong stiction

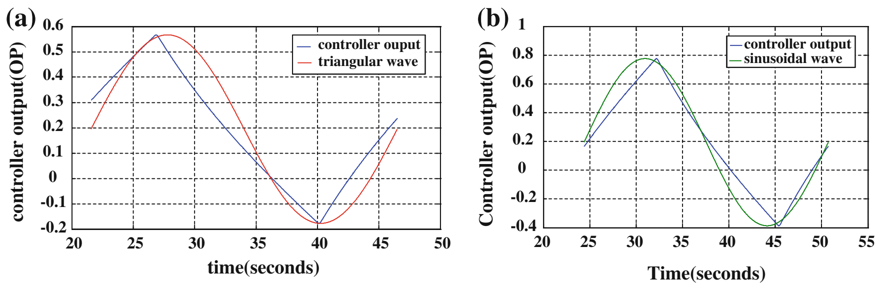

Fig. 5 **a** Response of curve fitting method for weak stiction, **b** response of curve fitting method for strong stiction

Table 2 Stiction index for different levels of stiction for curve fitting method

Magnitude of stiction	Stiction index
Weak stiction	0.5342
Strong stiction	0.8008

The above figure shows the process output and plant output produces triangle wave and the stiction valve produce the rectangular-shaped output. The above figs. 6a and 6b show the variations of controller output for weak stiction and strong stiction using sinusoidal fitting.

The single curve controller output is fitting with single curve triangular wave form, and the mean square error (MSE) value was calculated in weak stiction and strong stiction, the mean square error value was calculated in weak and strong stiction. The figs. 7(a) and 7(b) show the variations of controller output for weak stiction and strong stiction using triangular fitting. Stenman model is a single parameter model, the valve stiction band (d) is to be estimated by obtaining the difference between the actual stiction model output $y(t)$ and simulated stiction model output $y_m(t)$, and $u(t)$ is the system input signal that can be used in common to both the actual stiction model and simulated stiction model. The trajectories of estimated parameters for weak stiction and strong stiction shown in figs. 7(a) and 7(b)

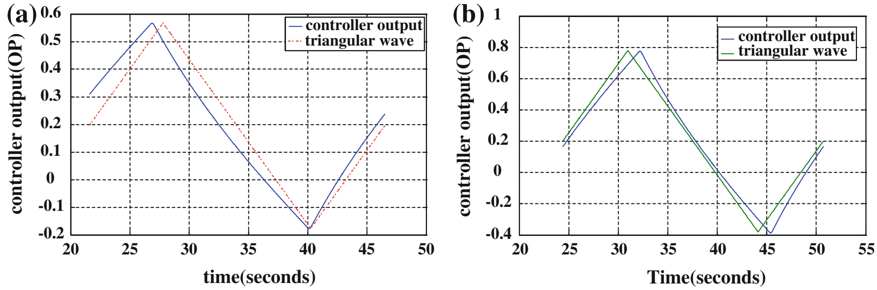

Fig. 6 **a** Response of curve fitting method for weak stiction, **b** response of curve fitting method for strong stiction

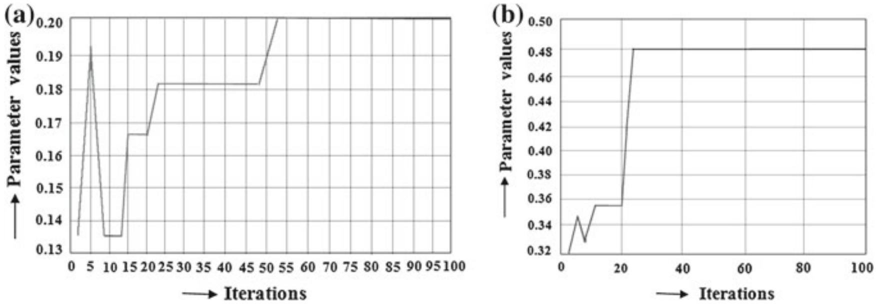

Fig. 7 **a** Trajectories of estimated parameters for weak stiction ($d = 0.2$), **b** trajectories of estimated parameters for strong stiction ($d = 0.5$)

The population and iteration values are 20 and 100, respectively. The parameter ‘d’ is initialized from 0.01 and is increased up to 10. The evaporation rate ρ is 0.2, and the parameter Q is 100. A control valve stiction model with weak stiction ($d = 0.2$), and strong stiction ($d = 0.5$) cases are simulated in the control loop.

Due to the presence of stiction the quantification of stiction is essential. The quantification of stiction is done by using ant colony optimization procedure [9]. By using ACO algorithm, the stiction parameters are estimated, when the objective function reaches the minimum value and the process is repeated for 100 iterations Table 3.

Table 3 ACO-based optimization

Magnitude of stiction	Actual stiction model parameter (d) value	Simulated stiction model parameter (d) value
Weak stiction	0.2	0.2
Strong stiction	0.5	0.48

It shows the parameter estimation is done by minimizing the objective function. The error, e(t), is the difference between actual strong stiction model output y(t) and the simulated strong stiction model output ym(t). It is used as the criterion to correct the model parameters, so as to estimate the parameters of the actual process. Here, 50 seconds time is taken to find the optimal value. The estimates of the recovered stiction model are very close to the true values.

8 Conclusion

In this paper, the dynamics of the stiction phenomenon found in the pneumatic control valve is understood by the physical model. The stiction found in the pneumatic control valve is modelled using first principles and implemented using MATLAB/Simulink software environment. The physical model involves several parameters, but the magnitude of stiction is based on the two parameters such as maximum static friction (fs) and Coulomb friction (fc). The closed-loop response for the physical model is obtained and the various detection methods such as the single curve piecewise fitting method implemented in the controller output. Due to the presence of stiction, the quantification of stiction is essential. The quantification of stiction is done by using ant colony optimization procedure. The ant colony optimization procedure involves certain steps to estimate the parameter values. The parameter estimation is done by minimizing the objective function. The error (e) is the difference between actual stiction model output (y) and the dynamic stiction model output (ym). It is used as the criterion to correct the model parameters, so as to estimate the parameters of the actual process.

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