Quantification of Nonlinear Valve Stiction Model Using Compound Evolution Algorithms

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ABSTRACT

The presence of oscillations in a control loop increases the deviations from the set point of the process variables, thus causing inferior products, larger rejection rates, increased energy consumption and reduced average throughput. There are several reasons for oscillations in control loops. They may be caused by excessively high controller gains, oscillating disturbances or interactions, but a very common reason for oscillations is friction in control valves. It is important to early detect valve stiction so that appropriate action can be taken to relieve the situation. In this paper a hybrid algorithm combines the fundamental elements of standard Genetic Algorithms with those proposed by Nelder and Mead in their Simplex algorithm. A nonlinear dynamic model consisting of a linear process and a nonlinear control valve with stiction is established. This approach involves obtaining easily measurable variables and using this information to estimate a set of unknown model parameters. By means of the hybrid algorithms proposed, the detailed procedure for the parameter identification with actual system's input-output data are given. The effectiveness of identification is verified by the comparison between actual values of system and model in different situations.

Keywords - : **Control valve stiction, genetic algorithms, simplex method, global optimization, parameters identification**

I. INTRODUCTION

Large-scale, highly integrated processing plants, such as oil refineries, ethylene plants, power plants, and rolling mills, 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. Therefore, control loops have been increasingly recognized as important capital assets that should be routinely monitored and maintained. The performance of the controllers, as well as of the other loop components, can thus be improved continuously, ensuring products of consistently high quality. Surveys [1, 2] indicate that about 20–30% of all control loops oscillate due to valve problems caused by valve non-linearities, such as stiction, hysteresis, dead band or dead zone. Many control loops in process plants perform poorly due to valve static friction (stiction) which is one of the most common equipment problems. It is well known that valve stiction in control loops causes oscillations in the form of periodic finite-amplitude instabilities, known as limit cycles. This phenomenon increases variability in product quality, accelerates equipment wear, or leads to control-system instability.

Several methods [3, 4, and 5] have been developed to detect valve stiction in the last decade. However, all these methods require either detailed process knowledge or user interaction which is not desirable for automated monitoring systems. Horch [5] presented an automatic detection method based the cross-correlation function (CCF) between the controller output (OP) and the process variable (PV) which is applicable to non integrating processes. He proposed another method to address the valve stiction in integrating processes by considering the probability distribution of the second derivative of controlled variable. In 2004, Singhal and Salsbury [6] proposed a valve stiction detection method based on the comparison of areas before and after the peak of an oscillating control error signal. Kano et al. [7] proposed two valve stiction detection methods, one requires knowing the valve position and the other is based on the plot of PV, OP with the shape of parallelogram. Jelali [8], introduced an identification method in which both linear and non linear sections of Hammerstein model can be estimated. The parameters of linear model were identified by using least square method and that of nonlinear stiction model were identified through experiments. Even though this method could identify all the parameters of process model including the nonlinear stiction, the parameters of linear model and nonlinear stiction model must be identified separately, which undoubtedly decreases the efficiency and accuracy of system identification. Due to these disadvantages, a new method which could identify the linear and nonlinear part models simultaneously is needed to increase the efficiency and accuracy of system identification Genetic Algorithms is a kind of stochastic search algorithm based on the rule of evolution of the biological universe. GA has the ability to search global optimal solution of the space without being trapped in local minima. This paper emphasizes the effectiveness of genetic algorithms and simplex method for identifying the parameters of nonlinear stiction model. GA is applied to conduct the global search and find promising regions of the search space, and then simplex method is adopted to conduct local search based on the search result of GA. Additionally, the initial value of simplex method is the search result of GA, so this algorithm can assure that the global optimal solution is searched out efficiently. The efficiency of parameter identification would be increased significantly, since the convergence speed of simplex method is very high. The paper is organized as follows. Section 2 describes the nonlinear Control valve stiction. The identification of nonlinear system based on GA and simplex method is proposed in section 3, which aims to improve the parameter identification accuracy and increase the efficiency of system identification. In section 4, through computer simulation, the efficiency and advantages of the proposed method are validated, and the identification results are verified in section 5 by using the input-output data of laboratory system.

II. CONTROL VALVE STICTION

Fig.1 shows the general structure of a pneumatic control valve. Stiction occurs when the smooth movement of the valve stem is hindered by excessive static friction at the packing area. The sudden slip of the stem after the controller output sufficiently overcomes the static friction caused undesirable effect to the control loop. Stiction, or high static friction, can be defined as the valve damage that keeps the stem from moving, as the static friction exceeds the dynamic friction. As a consequence, the force to move the stem is generally larger than the desired new stem value, and the movement is jumpy. A valve "suffering from stiction" will have phase plot as shown in Fig. 2, with four components such as deadband (DB), stick band (SB), slip jump (J) and moving phase (MP). The method assumes that the process and controller have linear behaviour, while the nonlinear behaviour in the loop is inserted by the sticky valve.

Fig.2 illustrates the input-output behaviour for control valve with stiction. The dash-dotted line represents the ideal control valve without any friction. Stiction consists of primarily of dead band, stick band, slip jump and the moving phase [9]. For control valve under stiction resting at point a, the valve position remains unchanged even when the controller output increases due to the dead band caused by the static friction. When the controller output exceeds the maximum static frictional force, f_S, the valve starts to respond. A slip jump of magnitude J is incurred when the valve starts to move at point b when the frictional force f_S convert to kinetic force f_D. From c to d, the valve position varies linearly. The same scenario happens when the valve stops at point d, and when the controller output changes direction. Parameter S represents the dead band plus stick band regions. Some simple relations of parameters can be observed from the fig. 2.

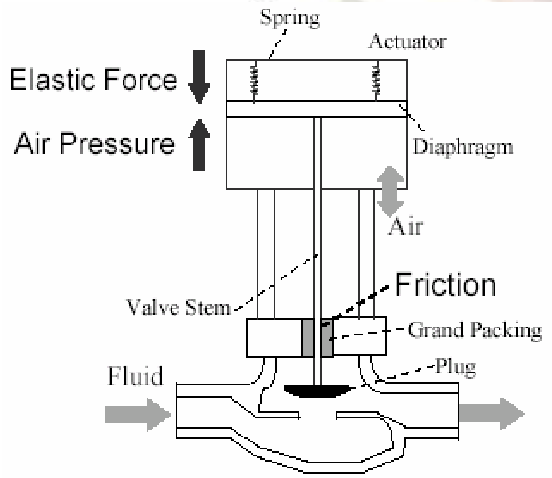


Fig.1 Structure of pneumatic control valve

$$
\begin{aligned}
S &= f_S + f_D \\
J &= f_S - f_D \\
Deadband &= 2\, f_D
\end{aligned}
\tag{1}
$$

Where f_S is the maximum static friction and f_D is kinetic friction.

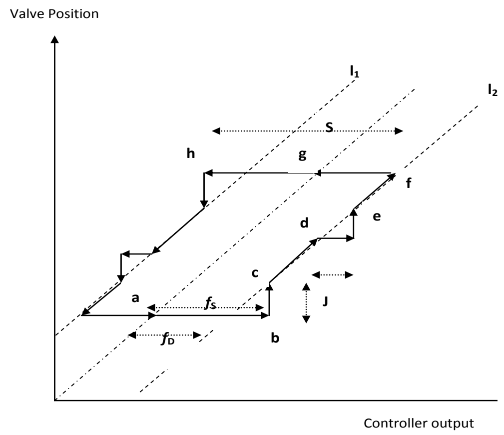


Fig.2 Input output Behaviour of Valve Stiction

The model used in this work is proposed by He et. al. [10], Fig.3 shows the flowchart of He's two parameter stiction model. Here $u(t)$ is the controller output, $u_v(t)$ is the valve position, u_1 is an intermediate variable, and the variable u_r is the residual force acting on the valve that has not materialized a valve move. He's two parameter model naturally handles both deterministic and stochastic signals, and is flexible in simulating different types of stiction by tuning f_S and f_D. It is worth noting that He's two-parameter model assumes that the valve stops at each sampling interval.

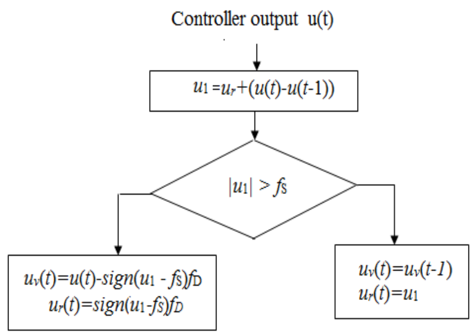


Fig.3 Flowchart of He's two parameter stiction model

III. IDENTIFICATION OF NONLINEAR VALVE STICTION BASED ON GA AND SIMPLEX METHOD

This section describes a method to compute both stiction parameters and plant model, using only normal operating data. Data from process variable (PV) and controller output (OP) are required. Here, only first order model is used. However, the methodology is adequate for second orders, integrating process and others also. The approach uses the following assumptions, which are quite similar to the other methods available in the literature:

- The plant model is (locally) linear.
- The loop nonlinearity is caused by the valve.
- The stiction model can be considered a Hammerstein model.

The proposed method computes both process and stiction parameters in a single step, using a hybrid optimization algorithm. This is the difference between this work and the work proposed by Jelali [8], where a two step procedure is used. The optimization problem for a first order model and that of control valve stiction model to be solved is:

$$J = \min (K, tau, f_S, f_D) \qquad (2)$$

Where K and 'tau' are process static gain and process time constant respectively f_S and f_D are valve stiction parameters. The proposed technique can be easily extended to higher order or integrating processes.

3.1 OPERATION OF GENETIC ALGORITHM PROCESS

Computationally simple yet powerful search algorithms, Genetic Algorithms (GAs) are search methods that seek to reproduce mathematically the mechanisms of natural selection and population genetics, according to the biological processes of survival and adaptation [17]. In solving problems by means of GA the following steps are carried out:

Step 1: Before applying GA procedure, an appropriate set of codes compatible with the nature of the problem is determined.

Step 2: A randomly selected initial population is formed.

Step 3: Combination value of each string in the initial population is calculated.

Step 4: In order to change the population and create new generation, crossover and mutation operators are used.

Step 5: The new population is evaluated and genetic algorithm procedure is carried out until the best solution value is reached.

3.2 NELDER MEAD SIMPLEX SEARCH METHOD

The Nelder-Mead simplex algorithm appeared in 1965 and is now one of the most widely used methods for nonlinear unconstrained optimization [18]. The Nelder-Mead method attempts to minimize a scalar-valued nonlinear function of n real variables using only function values, without any derivative information (explicit or implicit). The Nelder-Mead method falls in the general class of direct search methods. Four scalar parameters must be specifed to define a complete Nelder-Mead method: coefficients of *reflection* (ρ), *expansion* (χ), *contraction* (γ), and *shrinkage* (σ). These parameters should satisfy $\rho > 0$; $\chi > 1$; $\chi > \rho$; $0 < \gamma < 1$ and $0 < \sigma < 1$. Let $f(x)$ be the function for minimization. x is a vector in n real variables. Let, there are $n+1$ initial points for x and the following steps are carried out:

Step 1: (Order) Order the $n+1$ vertices to satisfy

$$f(x_1) \le f(x_2) \le \dots \le f(x_{n+1}),$$

using the tie-breaking rules given below.

Step 2:(Reflect) Compute the *reflection point* x_r from

$$x_r = \bar{x} + \rho(\bar{x} - x_{n-1}) = (1+\rho)\bar{x} - \rho x_{n-1} \qquad (3)$$

Where $\bar{x} = \sum_{i=1}^{n} x_i / n$ is the centroid of n best points. (all vertices except for x_{n+1}). Evaluate $f_r = f(x_r)$. If $f_1 \le f_r < f_n$, ecept the reflected point x_r and terminate the iteration.

Step 3:(Expand) If $f_r < f_1$, calculate the expansion point x_e,

$$x_e = \bar{x} + \chi(x_r - \bar{x}) = \bar{x} + \rho\chi(\bar{x} - x_{n-1}) = (1+\rho\chi)\bar{x} - \rho\chi x_{n-1} \qquad (4)$$

and evaluate $f_e = f(x_e)$. If $f_e < f_r$, accept x_e and terminate the iteration; otherwise (if $f_e \ge f_r$), accept x_r and terminate the iteration.

Step 4:(Contract) If $f_r \ge f_n$, perform a contraction between x and the better of x_{n+1} and x_r.

a. *Outside*. If $f_n \le f_r < f_{n+1}$ (i.e. x_r is strictly better than x_{n+1}), perform an outside contraction: calculate

$$x_c = \bar{x} + \gamma(x_r - \bar{x}) = \bar{x} + \gamma\rho(\bar{x} - x_{n-1}) = (1+\rho\gamma)\bar{x} - \rho\gamma x_{n-1} \qquad (5)$$

and evaluate $f_c = f(x_c)$. If $f_c \le f_r$, accept x_c and terminate the iteration; otherwise, go to step 5 (perform a shrink).

b. *Inside*. If $f_r \ge f_{n+1}$, perform an *inside contraction*: calculate

$$x_{cc} = \bar{x} + \gamma(\bar{x} - x_{n-1}) = (1-\gamma)\bar{x} + \gamma x_{n+1} \qquad (6)$$

and evaluate $f_{cc} = f(x_{cc})$. If $f_{cc} < f_{n+1}$, accept x_{cc} and terminate the iteration; otherwise, go to step 5(perform a shrink).

Step 5:(Perform a shrink step) Evaluate f at the n points

$$v_i = x_1 + \sigma(x_i - x_1) \qquad (7)$$

$i = 2, \dots, n+1$. The (unordered) vertices of the simplex at the next iteration consist of $x_1, v_2, \dots, v_{n+1}$.

The combination of local (Simplex method – Nelder & Mead) and global (Genetic Algorithms) search methods are used for identifying the parameters of the process and control valve stiction models. GA performs well for a global search and is capable of quickly finding promising regions of search space. In order to improve the efficiency of parameter identification, simplex method is applied to continue the optimization by using the search result of GA as its initial solution. In order to conduct system identification by using GA, the initial population and selection strategy need to be ascertained, and crossover, mutation, decode and individual evaluation also should be conducted. The best solution found by GA, according to a certain convergence criterion, here established as the number of generations, is used as the starting point for the Simplex method. Therefore, problems associated with the GA's slow convergence and the convergence to a local optimum can be reduced.

IV. SIMULATION RESULTS

The basic components of nonlinear system identification is as shown in Fig. 4; where, $u(k)$ is the input signal of actual system; $y(k)$ is the output signal of actual system; $\hat{y}(k)$ is the output signal of simulation system(Estimation); $e(k)$ is the error signal, which is used to compute the objective function. The optimization algorithms are used to adjust the parameters of the simulation system, which makes the error signal as small as possible.

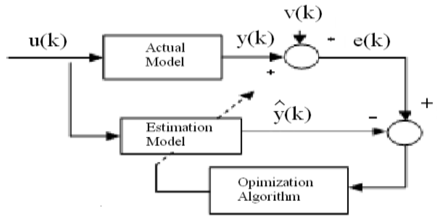


Fig.4 Frame work of parameter estimation

The parameters of GA and simplex algorithm are given in Table.1 and Table.2.

Table 1. Parameters of GA

Parameter	Values
Crossover probability(p_c)	0.6
Mutation probability(p_m)	100
Total generations of evolution(K_{max})	100
The size of population(M)	60

Table 2. Parameters of simplex algorithm

Parameter	Values
Contraction coefficient (γ)	0.5
Expansion coefficient(χ)	2
Initial step(h)	0.005
Reflection Coefficient(ρ)	1
Shrinkage Coefficient(σ)	0.5

The objective function is chosen as

$$F = \sum_{k=1}^{M} (y(k) - \hat{y}(k))^2 \quad (8)$$

Here M is the number of input-output data points used in the identification. The objective of this section is to show the applicability of the proposed method in a set of simulation studies. All simulations use a PI controller and a first order transfer function. The parameters of valve stiction model is identified by using actual input-output data, and the sampling period is 0.1s. The input-output data must reflect the real characters of the control valve stiction, which would increase the parameter identification accuracy. The time responses of Measured and Predicted process variables for three stiction cases are as shown in Fig.5, 6 and 7.

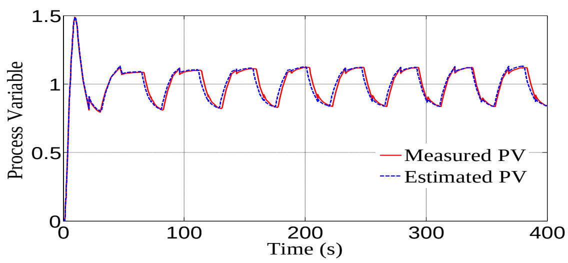


Fig. 5 Time response of Measured and Estimated Process Variable for Strong stiction

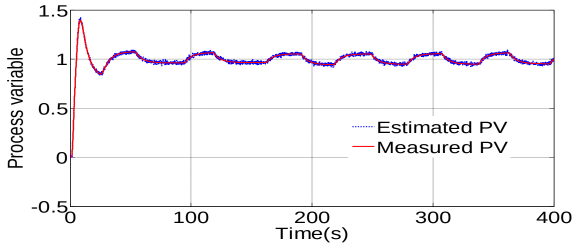


Fig.6 Time response of measured and Estimated Process variable for weak stiction

The actual and estimated stiction parameters along with process parameters are specified in table.3 The actual and estimated stiction parameters along with process parameters are specified in table.3

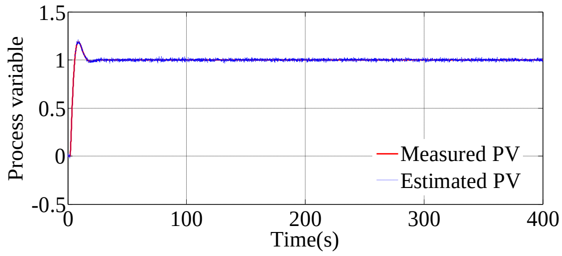


Fig.7 Time response of measured and Estimated Process variable for No stiction

A convergence plot of identified parameters by the Evolutionary programming and simplex methods for all types of stiction are shown in Fig.8,9 and 10. The input-output data must reflect the real characters of the control valve stiction, which would increase the parameter identification accuracy. The time responses of Measured and Predicted process variables for three stiction cases are plot of identified parameters by the Evolutionary programming and simplex methods for all types of stiction are shown in Fig.8,9 and 10. Noise has been added to the system response (10% of the process signal), since real system measurements are rarely smooth. The results are compared with conventional GA based optimization technique [8] and PSO based optimization technique[16].

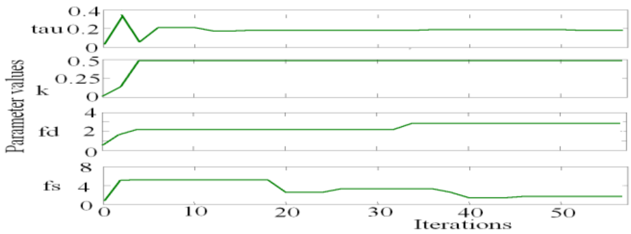


Fig. 8 Convergence trace of parameters for Strong stiction

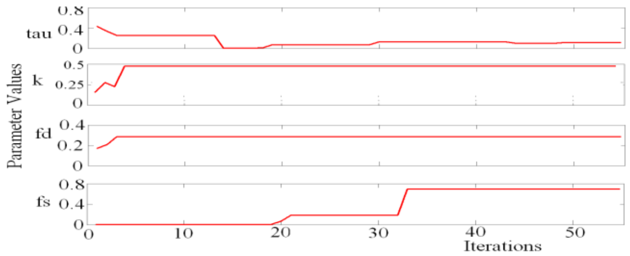


Fig. 9 Convergence trace of parameters for Weak stiction

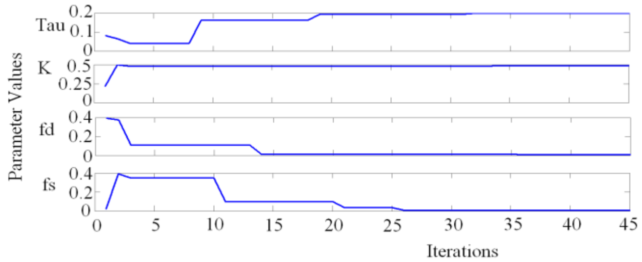
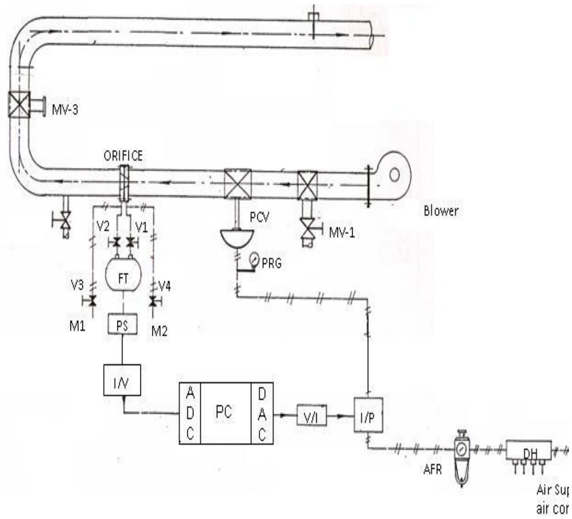


Fig. 10 Convergence trace of parameters for No stiction case

estimation problem are provided in Tables 3 and 4. From the tables it is inferred that GA with simplex method produce results that are extremely close to the actual value, with the PSO producing an output which appears closer to the actual than the GA.

V. REAL TIME IMPLEMENTATION

The objective of this section is to demonstrate the proposed framework and techniques on a laboratory air flow control system. The piping and instrumentation diagram of the process and its associated control system are shown in fig.11. The process variable (air flow rate) is sensed by differential pressure flow transmitter. This flow transmitter produces current output in the range of 4 to 20 mA. A current to voltage (I/V) converter is used to convert 4 to 20 mA into 1 to 5 volts. This measured voltage (Process Variable) is compared with the reference signal. The difference between the two is given as input to the controller. The controller used is a well tuned PID controller. The controller produces manipulating variable based on the difference between the set point and process variable. The manipulating variable in voltage form is converted into current by a Voltage/Current (V/I) converter. A Current/Pneumatic (I/P) converter is used to convert this current to pressure (3 to 15 psi) accepted by the control valve. The air failure to open (AFO) pneumatic control valve restricts the path of the air flow in the process pipe line, thus controlling the air flow rate. Controller output (OP) and process variable (PV) data are used for the identification procedure. The sampling time is taken as 0.1s. It is known a priori that the control valve in this control loop is having stiction. The results of this air flow control loop are plotted in Fig.12. The oscillation-detection algorithm applied to controlled signal shows significant oscillations. The identified stiction parameters indicate the presence of stiction, which is causing the sustained oscillations in the OP and PV signals. The utility of the proposed stiction estimation technique is illustrated in the laboratory flow control loop. In this case study, the number of cycles taken for the analysis lies in the range is 6 to 10. All computations reported in this study were carried out using MATLAB/Simulink. All open-loop and closed-loop simulations were accomplished using Simulink. To perform the optimization tasks, MATLAB was employed in conjunction with the Genetic Algorithm and Direct Search Toolbox, *i.e.* the GA function and the simplex functions. The stiction parameter estimates are found to be f_S=0.821 and f_D=0.392.



V1 to V4 - Manifold valves; FT - Flow Transmitter; MV-1 to MV-3 - Manual control valves; PS - Power Supply; M1 and M2 - Manometer connections; mA - Milliammeter; DH-De humidifier;I/P - Current to Pressure converter; AFR - Air Filter Regulator; PCV - Pneumatic Control Valve; PRG - Pressure Gauge ; G-2 - Galvanized pipe for cold air flow;

Fig. 11 Piping and Instrumentation Diagram of Laboratory Air Flow Control System

Table3. Estimated valve stiction parameters

Test condition	Actual Value		GA based optimization		PSO based optimization		GA and Simplex(Hybrid Evolutionary programming)	
	f_S	f_D	$\hat{f}_S$	$\hat{f}_D$	$\hat{f}_S$	$\hat{f}_D$	$\hat{f}_S$	$\hat{f}_D$
No Stiction	0	0	0.01	0.01	0.001	0.001	0.0001	0.0001
Weak Stiction	0.65	0.35	0.612	0.219	0.638	0.364	0.645	0.348
Strong Stiction	3	2	2.435	2.015	2.845	1.939	2.921	1.973

Table4. Estimated process parameters

Actual Value		GA based optimization		PSO based optimization		GA and Simplex	
K_p	*tau*	K_p	*tau*	K_p	*tau*	K_p	*tau*
0.5	0.2	0.472	0.187	0.488	0.215	0.499	0.199

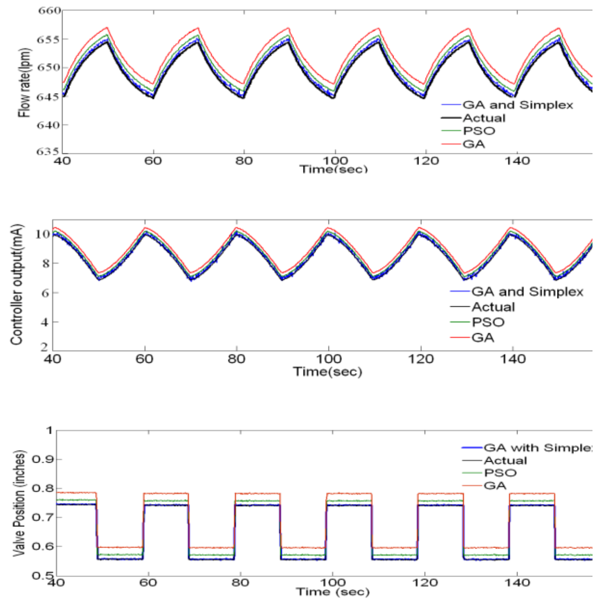


Fig.12 Response of air flow process with different optimization methods

VI. CONCLUSIONS

In this paper, GA and simplex method are used to identify the parameters of nonlinear valve stiction model. Using the global search ability of GA and the fast convergence of simplex method, the accuracy and efficiency of parameter identification are increased significantly. This method only uses a set of sufficient excitation input-output data of the actual system and can be extended to identify other nonlinear systems conveniently. The simulation results demonstrate the efficiency and correctness of the proposed method. The parameters of nonlinear valve stiction model are identified accurately, and the input-output data of actual system verify higher precision of the identification results by means of the method proposed. Results obtained show that simple step input can be used for effective system identification with much higher performance than conventional means.

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