PARAMETER ESTIMATION OF VALVE STICTION USING ANT COLONY OPTIMIZATION

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Abstract
In this paper, a procedure for quantifying valve stiction in control loops based on ant colony optimization has been proposed. Pneumatic control valves are widely used in the process industry. The control valve contains non-linearities such as stiction, backlash, and deadband that in turn cause oscillations in the process output. Stiction is one of the long-standing problems and it is the most severe problem in the control valves. Thus the measurement data from an oscillating control loop can be used as a possible diagnostic signal to provide an estimate of the stiction magnitude. Quantification of control valve stiction is still a challenging issue. Prior to doing stiction detection and quantification, it is necessary to choose a suitable model structure to describe control-valve stiction. To understand the stiction phenomenon, the Stenman model is used.
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 are 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.

Keywords:
Control Valve Stiction, Nonlinear System Identification, Stenman Model, Ant Colony Optimization

1. INTRODUCTION

Stiction in control valves and inadequate controller tuning are two of the major sources of control loop performance degradation. Stiction in a control valve appears as a hard non-linearity in the control loop dynamics [1]. Stiction is a sophisticated non-linear phenomenon. Its detection and quantification has been identified as a highly challenging academic as well as industrial problem. Several methods for detection and quantification of valve stiction have been presented in the literature. However, many of them have some practical limitations one way or other, which have to be addressed for real applications in industry. Hence, methods for valve stiction quantification and process model identification arise as important tools to treat loop performance problems.

Swarm intelligence (SI) is a type of artificial intelligence based on the collective behaviour of decentralized, self-organized systems. Two algorithms differentiated from foraging behaviours are Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Particle swarm optimization (PSO) is a swarm intelligence based algorithm to find a solution to an optimization problem in a search space, or model.

The Ant colony optimization Algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs.

Ant Colony Optimization (ACO) has been used extensively in solving many optimization searching problems. ACO is based on the concept of stigmergy which enables mobile-based agents called ants to collect and exchange information about the environment and solve the problem using collective intelligence. The idea of imitating the behavior of ants for finding good solutions to combinatorial optimization problems was initiated by Marco Dorigo in 1992.

The ACO is a relatively new approach to problem solving that takes inspiration from the social behaviours of ants. These ants deposit pheromones on ground in order to mark some favourable path that should be followed by other members of the colony.

Ant colony optimization exploits a similar mechanism for solving optimization problems. From the early nineties, when the first ant colony optimization algorithm was proposed, ACO attracted the attention of increasing numbers of researchers and many successful applications are now available, such as job shop scheduling, image processing and so on. In this paper, The Ant Colony Optimization (ACO) is introduced to identify all the parameters of the Stenman stiction model.

The organization of this paper is as follows: Section 2 starts out with the model of Stenman stiction, which is a one-parameter data-driven model.

In section 3, the ant colony optimization is introduced. This section also explains the flowchart and the characteristics of ACO.

The section 4 introduces the principle and implement of parameter estimation using ACO. The general procedure of ACO is also described.

In section 5, simulation results will be presented to evaluate the performance of the proposed technique.

2. VALVE STICTION MODEL

The present work focuses on pneumatic control valves, which are widely used in the process industry. 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.

The general structure of pneumatic control valve is shown in the below figure,

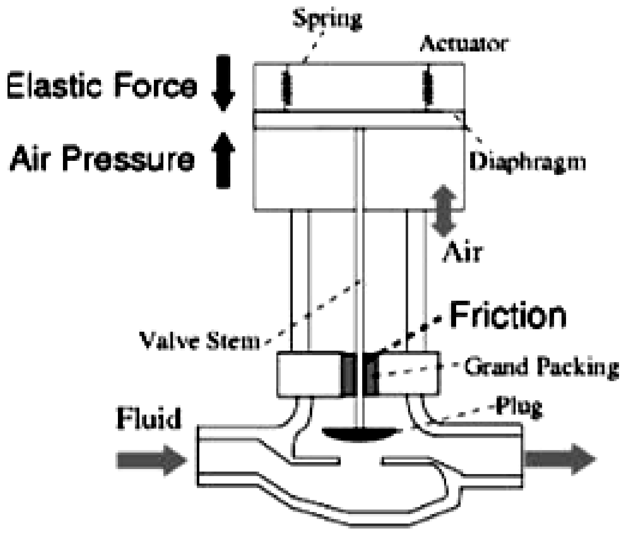

Fig.1. Structure of Pneumatic control valve

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 positioned.

2.1 MODELING VALVE STICTION

To understand the stiction phenomenon, two types of valve stiction model have been proposed in the literature. The physics-based model requires knowledge of quantities such as the mass of the moving parts and the friction forces that makes it infeasible for industrial studies or span of the valve input signal. Therefore, physical models of valve friction are not easily available for routine use.

The alternative choice is to use a data-driven stiction model, which is relatively simple and easy to understand and use in simulation. Two main classes of data-driven stiction models have appeared in the literature, they are termed one-parameter and two-parameter models. Several data-driven valve stiction-model structures are available in the literature [2].

2.2 ONE-PARAMETER STICTION MODEL

Stenman reported a single parameter stiction model. This simple model involves only one parameter (d) which is denoted as valve stiction band.

The mathematical expression of stenman model can be written as,

$$x\ t = \begin{cases} x\ t-1 & if \left| u\ t - x\ t-1 \le d \right| \\ u\ t & otherwise \end{cases} \quad (1)$$

where, $x(t - 1)$ and $x(t)$ represents past and present stem positions respectively, $u(t)$ is the actual controller output and d is the valve stiction band.

By considering various values for 'd', the results can be obtained for weak stiction and strong stiction. Since, Stenman model is a single parameter model, only the value of valve stiction band is taken into consideration.

Table.1. Values of 'd' for different levels of stiction

Magnitude of Stiction	D
Ideal valve	0
Weak stiction	0.2
Strong stiction	0.5

Since physical model has certain disadvantages, a single parameter data-driven model is used for quantifying stiction. 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 deadband. A real valve can stick anywhere whenever the input reverses direction.

3. ANT COLONY OPTIMIZATION

Ant Colony Algorithm was first introduced by E. Bonabeau and M. Dorigo in 1991, the algorithm is a simulation based evolution process of the real ant seeking food. In 1992, Dorigo used this method to solve the classic TSP, QAP problem. After then the algorithm has been widely used in Job-shop scheduling problem, assignment problem and the sort sequence (Sequential Ordering) knapsack problem, data clustering and so on [3].

3.1 BASIC PROCESS

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 [4].

It's an indirect, non-symbolic form of communication mediated by the environment: insects exchange information by modifying their environment by depositing pheromone. The original idea has since diversified to solve a wider class of Numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behaviour of ants.

The principle of these methods is based on the way ants search for food and find their way back to the nest. During trips of ants a chemical trail called pheromone is left on the ground. The role of pheromone is to guide the other ants towards the target point.

While building the solutions, each artificial ant collects pheromone information on the problem characteristics and uses this information to modify the representation of the problem, as seen by the other artificial ants.

The larger amount of pheromone is left on a route, the greater is the probability of selecting the route by artificial ants, and vice versa.

3.2 CHARACTERISTICS OF ACO

The ACO has several characteristics. In natures, the behaviour of the single ant is very simple, but the colony of the ant shows very complex behaviour in finding food. The single ant of the colony co-operates with each other through the pheromone which is chemical substance they leave on the ground while moving. In this way, the colony of the ant constitutes a system.

The ant colony is a distributed system. When the ant colony is going to complete one task, each ant does its utmost to work respectively and independently. The task is dependent on the work of each ant, but it is not completed not because of the defect of certain ant.

The ant colony is also a self organization system, so it possesses strong robustness. Finally it possesses not only positive regeneration but also negative feedback.

3.3 FLOWCHART OF BASIC ACO

The flowchart of the basic ant colony optimization was shown in the below figure.

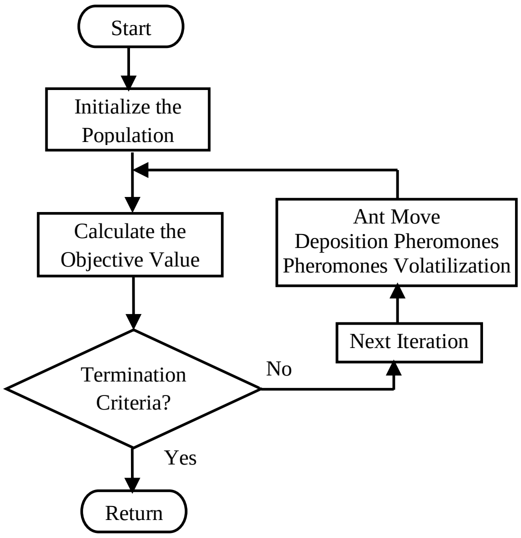

Fig.2. Flowchart of the basic ant colony optimization

The basic procedure of ACO involves certain steps to estimate the unknown parameters of the system. The first step is to initialize the population which represents the number of ants.

The main principle of ACO is to minimize the objective function which is also represented as fitness function [5].

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.

4. PRINICIPLE AND IMPLEMENT OF PARAMETER ESTIMATION USING ACO

This section presents a technique for quantification of stiction in control valves. To estimate the parameters of Stenman model, the principle and implement of parameter estimation are introduced in the section [5].

4.1 PRINICIPLE OF PARAMETER ESTIMATION

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 conditions [6].

The quantification is implemented by an ant colony optimization procedure. The open loop response is obtained for Stenman stiction model.

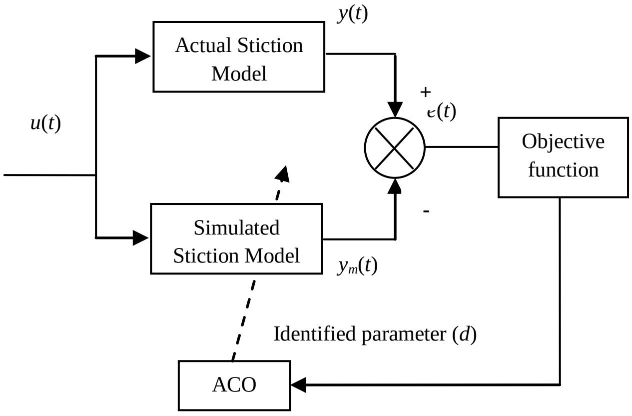

Fig.3. ACO based parameter estimation procedure

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

$$F = \sum_{t=1}^{M} \left(y(t) - y_m(t) \right)^2 . \tag{2}$$

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 $y_m(t)$ [8], [9].

4.2 ALGORITHM FOR PARAMETER ESTIMATION

Fig.3 depicts the programming steps of the basic ACO. The optimization action [10] is carried out by the ant colony optimization procedure as explained below.

The basic ACO algorithm is outlined as follows,

4.2.1 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

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
```

Fig.4. Programming steps of the basic ACO

4.2.2 Ant Solution Construction:

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

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_k} & where\, edge\ (i,j) \in T_k\ (t) \\ 0 & if\ edge\ (i,j) \notin T_k\ (t) \end{cases} \tag{3}$$

where, τ_{ij} is the trail intensity which indicates the intensity of the pheromone on the trail segment (ij), Q represents the Pheromone quantity

4.2.3 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,

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{4}$$

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 an ant completes its tour, the local pheromone updating is done. The value of $\Delta\tau_j$ is defined as follows,

$$\Delta\tau_j = \frac{1}{T_{ik}} \tag{5}$$

where, T_{ik} is the shortest path length that searched by k-ant at i-th iteration.

When an 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,

$$\Delta\tau_j = \frac{D}{T_{op}} \tag{6}$$

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

4.3 ACO BASED IDENTIFICATION ALGORITHM

The ACO based identification algorithm is can be summarized in the following steps:

Step 1: M input-output data points are generated from the system to be identified.

Step 2: Random initial values for parameters of the nonlinearities in the appropriate range are generated.

Step 3: The objective function for each particle in the initial population is evaluated.

Step 4: When objective function is evaluated, update the pheromone according to formula (4) – (6).

Step 5: If all the ants end their trip, continue to step6. Otherwise repeat step (3). The objective function to the new searching points and the evaluation values are calculated.

Step 6: $N_c = N_c + 1$, calculate the current optimal solution.

Step 7: Judge if it satisfies the iterative condition $N_c > N_{cmax}$, If it satisfies, end the iteration and output the best solution, else return to Step2 until satisfy the iterative condition.

The stiction parameter (d) of simulated stiction model is initialized from 0.01 to estimate the actual stiction parameter.

5. RESULTS AND DISCUSSION

The Stenman stiction model is simulated for various values of'd' to obtain the results for weak stiction and strong stiction. First, the dynamics of stiction is obtained using the one-parameter model and is modelled using MATLAB/ Simulink software.

The open loop response patterns of Stenman model are shown in Fig.5 and Fig.6 with the stick-slip properties of valves. The range of operation is reduced in the strong stiction when compared to the weak stiction. It represents that, the whenever the percentage of stiction is increased, the valve stem movement is reduced. According to the algorithm mentioned above, the Stenman stiction model parameter estimation is simulated with the ACO algorithm which is coded and open loop simulations are carried out. All the computations reported in this study are carried out using MATLAB and Simulink.

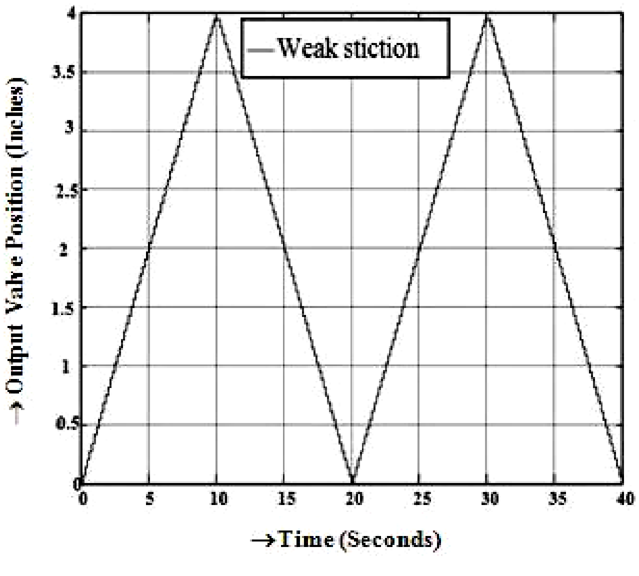

Fig.5. Open loop response for Stenman model in the case of weak stiction (d=0.2)

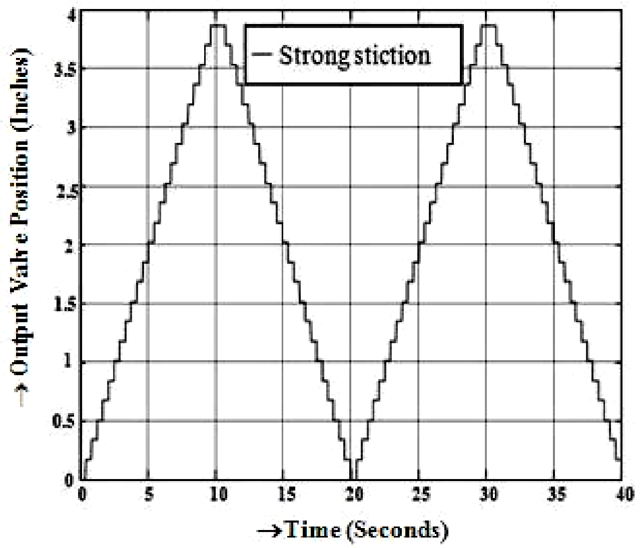

Fig.6. Open loop response for Stenman model in the case of strong stiction (d=0.5)

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.

Table.2 lists the test conditions and results for weak and strong stiction cases. The trajectories of the estimated parameters (d) for weak and strong stiction are shown in Fig.6 and Fig.7 respectively.

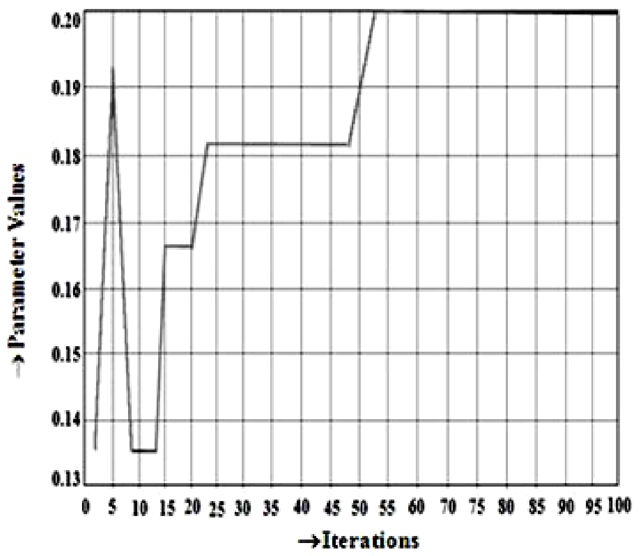

Fig.7. Trajectories of estimated parameters for weak stiction (d = 0.2)

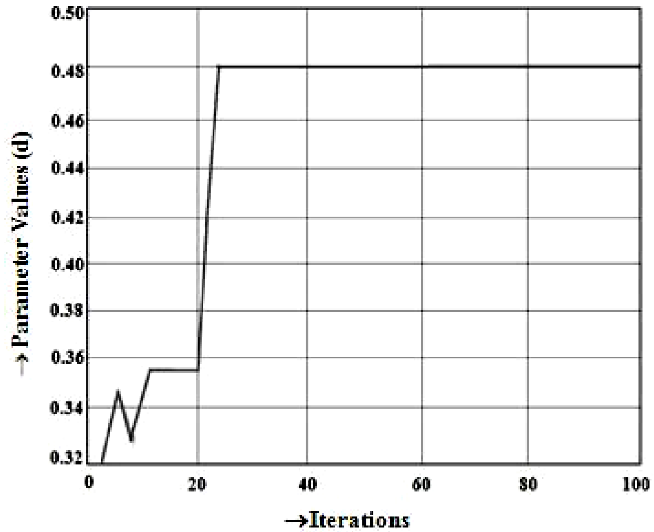

Fig.8.Trajectories of estimated parameters for strong stiction (d=0.5)

Due to the presence of stiction the quantification of stiction is essential. The quantification of stiction is done by using ant colony optimization procedure. 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.2. Parameters of ACO algorithm

Magnitude of Stiction	**Model Parameter d(%)**	
	Actual Stiction Model	**Simulated Stiction Model**
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 $y_m(t)$. It is used as the criterion to correct the model parameters, so as to estimate the parameters of the actual process. The estimates of the recovered stiction model are very close to the true values.

6. CONCLUSION

In this paper, the ant colony optimization was used to identify the parameters of the Stenman stiction model. A novel open-loop stiction quantification method is presented based on an open-loop model-identification approach. The approach uses OP signals to estimate the parameters of a Stenman model consisting of a single parameter (d). The Stenman model identification problem has been formulated as an optimization problem and Ant Colony Optimization is used to estimate the unknown parameters from input-output data.

Thus, Ant colony algorithm as a distributed optimization algorithm, it has demonstrated its superior ability to search the optimal solution for a variety of combinatorial optimization. It is also shown that the identification by this method is easy in computation and can give accurate estimated models even in the presence of the measurement noises.

A cost effective optimization technique is adopted to find the best valve-stiction models representing more realistic valve behaviour in the oscillating control loop. It can be concluded that the present technique accurately quantify stiction.

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