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Actuator Hysteresis Identification and Compensation Using An Adaptive Search Space Based Genetic Algorithm

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ABSTRACT

A proposed *Genetic Algorithm with Adaptive Search Space* (GAASS) is applied to identify the hysteresis parameters of an electromechanical-valve actuator installed on a pneumatic pipeline system. According to the normalized fitness distance in each generation, the proposed GAASS method consistently identifies the best search domains in the parameter space and adjusts the crossover and mutation rates in order to achieve fast convergence and high accuracy. Experiments have been conducted to investigate the effectiveness of the proposed hysteresis identification and compensation approach with three different types of sensor measurements, and the results are reported in this paper.

Index Terms – Adaptive search space, adaptive crossover, adaptive mutation, genetic algorithms, and actuator hysteresis identification.

1. INTRODUCTION

Actuator hysteresis often leads to problems in control systems because it creates tracking errors, limit cycles, and undesired stick-slip motions. Hysteresis exists in electrical valve actuators, mainly due to the ferromagnetic effect [1, 2] associated with the motor drive. To counteract hysteresis, a hysteresis model is required in designing a control compensator, and the identification of hysteresis model parameters is essential. Conventional model-based identification methods such as, the least square approximation of Preisach models [3], the interacting multiple model (IMM) approach using a Kalman filter to identify static hysteresis models [4] require derivative calculations of the objective function with respect to hysteresis parameters and cannot be easily applied to highly non-linear and high-dimensional models. Recent research on hysteresis parameter identification involves the use of stochastic algorithms such as GAs and EAs, and new methods have been developed to improve the robustness in practical applications [5].

In this paper, a proposed *Genetic Algorithm with Adaptive Search Space* (GAASS) is implemented for the parameter identification of the Krasnosel'skii's hysteron hysteresis model of an electrical valve actuator installed on a pneumatic system. With the proposed GAASS, the search space is adaptively updated to achieve high search accuracy. The best search domains in the parameter space are identified according to the normalized fitness distance in each generation, and the crossover and mutation rates are adjusted accordingly in order to achieve fast convergence and high accuracy. Three types of sensors (actuator position, air pressure and mass airflow rate) are used. The experimental results have demonstrated the effectiveness of the proposed approach.

The paper is organized as follows: Section 2 defines the employed hysteresis model; Section 3 describes the parameter identification procedure; Section 4 provides the experimental results; and Section 5 concludes the paper.

2. HYSTERESIS MODEL

Hysteresis models have been developed in various ways such as the Bouc-Wen model, Chua-Stromsmoe model, Preisach model, and Krasnosel'skii's hysteron, etc [6]. Among them, Krasnosel'skii's hysteron provides a general model of hysteresis which captures most of the hysteretic characteristics and is applicable for parametric inverse compensation. A piecewise linear hysteron model described using eight parameters is selected for our work, and the sets of equations to describe Krasnosel'skii's hysteron are derived by Tao and Kokotović [2]:

$$
H(v(j)) = u(j)
$$
$$
= \begin{cases} u(j-1) & \text{if } v(j) = v(j-1) \\ m_{h,t}v(j) + c_{h,t} & \text{if } v(j) \ge v_1, \text{ or} \\ & \text{if } m_{h,t} < m_{h,b}, \\ & u(j-1) = m_{h,t}v(j-1) + c_{h,t} \text{ and} \\ & v(j-1) < v(j) < v_1 \\ m_{h,b}v(j) + c_{h,b} & \text{if } v(j) \le v_2, \text{ or} \\ & \text{if } m_{h,t} > m_{h,b}, \\ & u(j-1) = m_{h,b}v(j-1) + c_{h,b} \text{ and} \\ & v_2 < v(j) < v(j-1) \\ m_{h,t}v(j) + c_d & \text{if } v_d < v(j) < v(j-1) \\ m_{h,b}v(j) + c_u & \text{if } v(j-1) < v(j) < v_u \\ m_{h,l}(v(j) - c_{h,l}) & \text{if } v_d \ge v(j) \ge v_2 \\ m_{h,r}(v(j) - c_{h,r}) & \text{if } v_u \le v(j) \le v_1 \end{cases} \quad (1)
$$
$$
\text{subject to: } m_{h,l} > 0, m_{h,r} > 0, \min(m_{h,l}, m_{h,r}) > m_{h,t} > 0,
$$
$$
\min(m_{h,l}, m_{h,r}) > m_{h,b} > 0, c_{h,l} < c_{h,r}, c_{h,t} > c_{h,b}
$$

where the eight parameters contain four slopes $m_{h,l}$, $m_{h,r}$, $m_{h,t}$, $m_{h,b}$ and four crossings $c_{h,l}$, $c_{h,r}$, $c_{h,t}$, $c_{h,b}$ at the left, right, top, and bottom sides of the hysteresis loop indicated by the subscripts l, r, t, b respectively. The index j denotes the sampled data number, the functions $v(j)$ and $u(j)$ denote input and output, and the variables v_1, v_2, v_u, v_d are given by:

$$v_1 = \frac{c_{h,t} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,t}}, \quad v_2 = \frac{c_{h,b} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,b}} \tag{2}$$

$$v_u = \frac{m_{h,r}c_{h,r} + c_u}{m_{h,r} - m_{h,b}}, \quad v_d = \frac{m_{h,l}c_{h,l} + c_d}{m_{h,l} - m_{h,t}} \tag{3}$$

where in Eq. (3), $c_u = u(j-1) - m_{h,b}v(j-1)$ and $c_d = u(j-1) - m_{h,t}v(j-1)$ such that $v_4 \le v_d \le v_u \le v_3$.

3. HYSTERESIS PARAMETER IDENTIFICATION USING GAASS

3.1 Parameter Identification Procedure

The parameter identification problem is generally defined as identifying a parameter set $x \in \boldsymbol{X}$ when the output data $y \in \boldsymbol{Y}$ and a direct mapping $\psi: \boldsymbol{X} \to \boldsymbol{Y}$ are known. The parameter space is given by:

$$\boldsymbol{X} = \{x \in \boldsymbol{X_1} \times \ldots \times \boldsymbol{X_m} \mid g_i(x) \ge 0, \; \forall\, i \in \{1, \ldots, m\}\} \tag{4}$$

where m represents the number of parameters and g_i: $\boldsymbol{X_1} \times \ldots \times \boldsymbol{X_m} \to \Re^m$ represents the inequality constraints. Mapping $\boldsymbol{X}$ to $\boldsymbol{Y}$, the input-output relation can be expressed as:

$$y = \psi(x) + e \tag{5}$$

where e represents the error term.

The parameter identification method, through the continuous adaptation of the parameters, minimizes the objective function

$$J = \sum_{i=1}^{n} |e_i|^2 = \sum_{i=1}^{n} |y_i - \psi_i(x)|^2 \tag{6}$$

where n is the total number of data points. The adaptation of the system parameters is performed using the proposed GAASS, which searches for a set of parameters that lead to a smaller J until the maximum generation is reached and/or the relative percentage error, $\%e_r$, falls below a predefined error bound. The $\%e_r$ is given by:

$$\%e_r = \sqrt{\frac{J}{\sum_{i=1}^{n} |y_i|^2}} \times 100\% \tag{7}$$

3.2 The Plant

The general structure of the actuator hysteresis identification applied in our pneumatic pipeline system is illustrated in Fig. 1. In Fig. 1, v represents the actuator current command; H represents the actuator hysteresis;

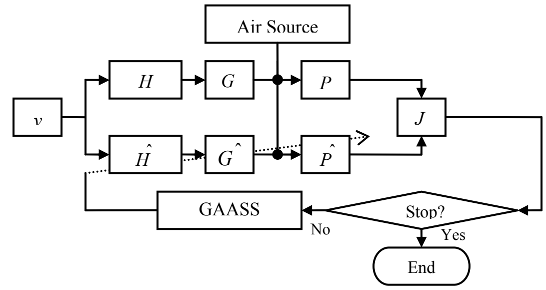

Fig. 1 Actuator hysteresis identification using GAASS

$\hat{H}$ is the mapping model (ψ) represented by Krasnosel'skii's hysteron; G and $\hat{G}$ represent the actual dynamics and mathematical model of the electromechanical-valve actuator; P and $\hat{P}$ represent the actual dynamics and mathematical model of the pneumatic pipeline that is instrumented with a pressure transducer and a thermal flow sensor.

The pressure transducer measures the pressure upstream the valve, p_1. Due to the impedance of the pipeline, p_1 actually follows closely with a first-order system which can be described by $\hat{p}_1$ as:

$$\hat{p}_1(t) = \mathscr{L}^{-1}\left[\frac{p_1(s)}{\tau s + 1}\right]; \quad [0 < \tau < 1] \tag{8}$$

where τ is a time constant to be identified from experiment.

The thermal flow sensor provides an alternative of the plant output by measuring the mass flow rate, W, through the pipeline. Experimental results have suggested that the flow sensor dynamics closely follows the second-order system which can be described by $\hat{W}$ as:

$$\hat{W}(t) = \mathscr{L}^{-1}\left[\frac{W(s)\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}\right]; \; [0 < \zeta < 1 \, (\text{underdamped})] \tag{9}$$

where the damping ratio ζ and the natural frequency ω_n are parameters to be identified from experiment.

Due to the fact that the original position feedback controller does not provide backlash compensation, the actuator exhibits an actuation backlash which can be described by the function, $u = B(m_b, c_{b,l}, c_{b,r}, v)$ as:

$$B(v(j)) = u(j) = \begin{cases} m_b\left(v(j) - c_{b,l}\right) & \text{if } v(j) \le v_l \\ m_b\left(v(j) - c_{b,r}\right) & \text{if } v(j) \ge v_r \\ u(j-1) & \text{if } v_l < v(j) < v_r \end{cases} \tag{10}$$
$$\text{subject to}: m_b > 0, c_{b,l} < c_{b,r}$$

where m_b, $c_{b,l}$, $c_{b,r}$ are parameters to be identified, which represent the slope, zero-crossing at the left, and zero-crossing at the right of the backlash operator respectively. The variables $v_l = u(j-1)/m_b + c_l$ and $v_r = u(j-1)/m_b + c_r$ indicate the change of input directions.

Hence, cascading all the parts from (1), (8) or (9), and (10) to form the structure in Fig. 1, the parameter space dimension of the actuator hysteresis identification extends to 12 if the pressure transducer signal is used and 14 if the flow sensor signal is used as the plant output.

3.3 The GAASS Method

The proposed GAASS incorporates an adaptive mechanism in defining the search space of the genetic algorithm (GA). It is a method added to the traditional GAs to enhance their heuristic search power. The GAASS uses the real-number encoding which requires much less memory than the traditional GAs.

There are five major operators in the computation framework of GAASS: *initialization*, *evaluation*, *selection*, *crossover*, and *mutation*. Except for initialization which only performs once in the entire procedure, all the other four operators execute in every generation until the stop criterion is met. The following describes the various operators of the GAASS including the initialization method, adaptive search space method, selection scheme, and the adaptive crossover and mutation schemes:

1) *Initialization*: The initial real-number chromosomes are randomly generated from within the feasible region (constraints) of each system parameter. It uses the *rejecting strategy* [7] in handling the constraints of the parameters. Rejecting strategy discards all infeasible chromosomes (solutions that violate the constraints) created throughout the evolutionary process. The initial population size, N_{ipop}, is set to twice the size of the population in the latter generations, N_{pop}. Through the *tournament* selection in the *selection* operator, only those chromosomes with higher fitness from the initial population are taken to the second generation while those with lower fitness are discarded. This initialization method gives the algorithm a nice start by providing a fine initial sampling of the parameter space.

2) *Evaluation*: The evaluation of the *fitness function*, *selection probability* p_k, and *expected value* e_k of each chromosome, as well as the *Normalized Fitness Distance* (*NFD*) are performed in this operator.

Fitness function is the *objective function* of the algorithm, J, that is to be minimized. The selection probability p_k and the expected value e_k are used for the selection of chromosomes in the *selection* operator. For chromosome $k \in [1, N_{pop}]$ with fitness f_k, the values of p_k and e_k are determined by:

$$p_k = f_k \Big/ \sum_{i=1}^{N_{pop}} f_i \tag{11}$$

$$e_k = N_{pop} \times p_k \tag{12}$$

The *Normalized Fitness Distance* (*NFD*) is a measure of the solution convergence. It is analogous to the ratio of the improvement of average fitness to the improvement of the best fitness in a population. It controls the adaptive search space mechanism as well as the exploration and exploitation pressures of GAASS. *NFD* is defined by:

$$NFD = \begin{cases} \dfrac{f_{max} - \bar{f}}{f_{max} - f_{min} + \varepsilon} & \textit{for minimization problem} \\ \dfrac{\bar{f} - f_{min}}{f_{max} - f_{min} + \varepsilon} & \textit{for maximization problem} \end{cases} \tag{13}$$

where $f_{\max}$ is the maximum fitness value of the population, $f_{\min}$ is the minimum fitness value of the population, $\bar{f}$ is the average fitness value, and ε is a small positive number to prevent the equation from zero division. If *NFD* of the present population is smaller than or equal to that of the previous population (solution converges), the size of the adaptive search space, $\mathbf{\Omega}$, will be reduced. Otherwise (solution diverges), it will remain the same as that of the previous population. The average of each parameter in the current population, $\bar{x}$, is used as the origin of $\mathbf{\Omega}$. Then, the search space $\mathbf{\Omega} \in \Re^m$ is expressed as:

$$\begin{aligned} \mathbf{\Omega} &= \prod_{i=1}^{m} \left[\max\{C_{lower,i}, D_{lower,i}\}, \min\{C_{upper,i}, D_{upper,i}\} \right] \\ &= \prod_{i=1}^{m} \left[\max\{C_{lower,i}, (\bar{x}_i - \gamma_i)\}, \min\{C_{upper,i}, (\bar{x}_i + \gamma_i)\} \right] \end{aligned} \tag{14}$$

where D_{lower} is the lower bound of $\mathbf{\Omega}$, D_{upper} is the upper bound of $\mathbf{\Omega}$, γ is the half search domain, and m is the number of parameters. γ starts with half of the parameter constraint, $\gamma_{i,init}$, then it gradually reduces dynamically according to the exponential function defined by:

$$\gamma_i(z) = \gamma_{i,init} \exp(-cs) \quad \forall i \in \{1,...,m\}, z \in \{1,...,gen\} \tag{15}$$

where z is the generation count, gen is the maximum number of generation, c is a positive, problem-dependent coefficient which controls the contracting rate of the search space, and s is the search space index given by:

$$s = \begin{cases} 1 & \text{if } z = 1 \\ s+1 & \text{if } NFD(z) \le NFD(z-1) \quad \forall z \in \{1,...,gen\} \\ s & \text{if } NFD(z) > NFD(z-1) \quad \forall z \in \{1,...,gen\} \end{cases} \tag{16}$$

If D_{lower} falls outside the parameter constraint, it will be replaced by the lower bound constraint C_{lower}. This is also true for D_{upper}, where it will be replaced by the upper bound constraint C_{upper}. This adaptive search space method provides the appropriate search region for the regeneration of chromosomes in *crossover* and the regeneration of genes in *mutation* to take place.

3) *Selection*: Selection is done using the *remainder stochastic sampling*. This *mixed sampling* approach contains both stochastic and deterministic features simultaneously [7]. To further improve the convergence performance, the *elitist selection* scheme is also used to ensure that the best chromosome is always passed onto the next generation.

4) *Crossover*: Crossover is the main search operator in GAs which performs the exchange of information among chromosomes through combination and disruption of schemata. Investigations in [8] suggested that the essence of effective crossover is to increase both the combination power and the disruption power. In GAASS, the increase of combination power and disruption power is achieved using an adaptive crossover rate scheme. The number of mating takes place in a population is controlled by the adaptive crossover rate, p_c, which changes according to *NFD*. If *NFD* of the present population is smaller than or equal to that of the previous population, p_c is set to a higher value, $p_{c,h}$. Otherwise, p_c is set to a lower value, $p_{c,l}$. The adaptive crossover rate scheme is described as:

$$p_c = \begin{cases} p_{c,h} & \text{if } NFD(z) \le NFD(z-1) \quad \forall z \in \{1,\ldots,gen\} \\ p_{c,l} & \text{if } NFD(z) > NFD(z-1) \quad \forall z \in \{1,\ldots,gen\} \end{cases} \tag{17}$$

where the values of $p_{c,l}$ and $p_{c,h}$ are set to 0.5 and 0.9, respectively. According to Eq. (17), the number of offspring that will be generated in a population, N_c, is given by:

$$N_c = N_{pop} \times p_c \tag{18}$$

The maximum number of offspring that can be generated in a population is equal to its population size N_{pop}. If the number of offspring generated is fewer than the maximum, GAASS will perform the chromosome *regeneration* around the origin of $\mathbf{\Omega}$ to fill the vacancy according to the following equation:

$$x_{k,i}(z) = \bar{x}_i(z) + r(\gamma_i(z)) \quad \forall i \in \{1,\ldots m\}, z \in \{1,\ldots gen\}, k \in \{(N_c+1),\ldots N_{pop}\} \tag{19}$$

where $r \in [-1, 1]$ is a random floating-point number. The adaptive crossover rate scheme ensures that there are always enough combination power and disruption power in a population to perform effective crossover. When the solution converges, the combination power is increased by the higher crossover rate such that the majority of offspring are produced from the weighted averages of the parents. When the solution diverges, the disruption power is increased by the higher regeneration rate of chromosomes inside $\mathbf{\Omega}$ such that some new, unbiased chromosomes that could not be produced by the previous genetic operators can be introduced. The role of chromosome regeneration here serves two purposes: First, during early generations where the size of $\mathbf{\Omega}$ is relatively large and the Euclidean distance between the global optimum and the origin of $\mathbf{\Omega}$ is relatively long, regeneration performs a more stochastic search in $\mathbf{\Omega}$, which hopefully provides better chromosomes for the latter generations. Second, during latter generations where the size of $\mathbf{\Omega}$ is relatively small and the Euclidean distance between the global optimum and the origin of $\mathbf{\Omega}$ is relatively short, regeneration performs a more heuristic search in $\mathbf{\Omega}$, which helps exploiting the better solution.

The crossover procedure employs the two-parent crossover scheme which is performed by the combined method of the *arithmetic crossover* and the *schema processing* [5]. This combined method takes the advantage of the binary GA mating scheme.

(5) *Mutation*: Mutation serves as a background operator to restore genetic materials as well as a local optimizer since it is a guided-search operator controlled by $\mathbf{\Omega}$. Mutation rate is significant in the controlling of the GA performance because it induces diversity to a population and also exploits the better solution. In GAASS, the mutation rate, p_m, defined as the number of parameters chosen to mutate in a population is changed adaptively according to *NFD*. If *NFD* of the present population is smaller than or equal to that of the previous population (solution converges), p_m is set to a higher value, $p_{m,h}$, such that the diversity of chromosomes is increased so to avoid premature convergence. Otherwise (solution diverges), p_m is set to a lower value, $p_{m,l}$, since the population already has enough diversity. The adaptive mutation rate scheme is described as:

$$p_m = \begin{cases} p_{m,h} & \text{if } NFD(z) \le NFD(z-1) \quad \forall z \in \{1,\ldots,gen\} \\ p_{m,l} & \text{if } NFD(z) > NFD(z-1) \quad \forall z \in \{1,\ldots,gen\} \end{cases} \tag{20}$$

where the values of $p_{m,l}$ and $p_{m,h}$ are set to 0.01 and 0.3, respectively. According to Eq. (20), the number of mutations performed in a population, N_m, is given by:

$$N_m = N_{pop} \times m \times p_m \tag{21}$$

The mutation procedure is performed by randomly generating a value that falls within the subspace of $\mathbf{\Omega}$, $\boldsymbol{\omega}$, for each chosen parameter (gene) until the number of mutations has reach the maximum, N_m. The subspace $\boldsymbol{\omega}$ defines the range of local optimization and is given by:

$$\boldsymbol{\omega} = \xi \mathbf{\Omega} \tag{22}$$

where ξ is a problem-dependent coefficient which defines the range of perturbation of each gene. Depending on the parameter sensitivity, the value of ξ usually ranges from 0.01 to 0.05.

The effectiveness of the proposed GAASS method has been compared with that of the traditional Simple Genetic Algorithm (SGA) using three commonly used test functions. Detailed results can be found in [9]. One of the three test functions, $F1$, is given here:

$$F1(x_1, x_2) = \sum_{i=1}^{5} i\cos[(i+1)x_1 + i] \sum_{i=1}^{5} i\cos[(i+1)x_2 + i]; \quad x_i \in [-10,10] \forall i \in \{1,2\}; \quad \text{Global optima} = 186.7307 \tag{23}$$

Using a population size (N_{pop}) of 6 and a generation number (gen) of 100 while maintaining the same rates of crossover and mutation defined in Eq. (17) and (20), both the SGA and the GAASS have been run ten times using random seeds from 0 to 9. The corresponding results are shown in Fig. 2 (Note that only the best of the ten SGA optimization results is shown.). As seen from Fig. 2, the GAASS method has clearly outperformed the SGA in both the convergence speed and the solution accuracy.

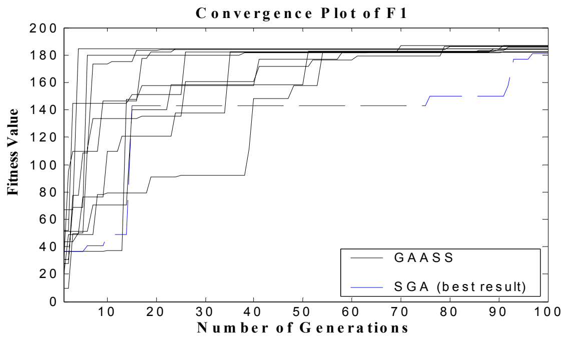

Fig. 2 *F*1 convergence comparison

4. EXPERIMENTAL RESULTS

Experiments have been conducted to evaluate the effectiveness of the proposed method. The apparatus of the experiment consists of two major parts: a command unit and a pneumatic pipeline system. The command unit consists of a PC with A/D and D/A boards. The PC serves as the controller and sends out current command with the induced actuator hysteresis having the properties: $m_{h,l}$ = 1.01, $m_{h,r}$ = 1.05, $m_{h,t}$ = 0.10, $m_{h,b}$ = 0.15, $c_{h,l}$ = -0.25, $c_{h,r}$ = 0.50, $c_{h,t}$ = 14.00, and $c_{h,b}$ = 7.00. The PC also collects measurements from an actuator position sensor, a static pressure transducer, and a thermal flow sensor. The position sensor signal serves as the reference here.

The pneumatic pipeline system consists of a single-stage air compressor, two 180-Gal pressure vessels, a ¾"-ID ABS airline section, a 2"-ID PVC pipe section, and a 1"-ID manual brass ball valve. The pressure vessels are fed by a compressor and provide compressed air of 100 psig at room temperature. The airflow inside the pneumatic pipeline is controlled using a ¾"-ID brass ball valve driven by an electromechanical actuator. Along the pipeline, the static pressure transducer is installed upstream of the control valve while the thermistor flow sensor is installed downstream of the control valve.

The experiment procedure was started by turning on the upstream manual ball valve to allow a total pressure of 30 psig maintained upstream of the valve. Then, the current command was sent from the PC via the D/A board to the actuator. At the same time, the output signals from the position sensor, pressure transducer, and thermal flow sensor were acquired simultaneously by the PC via the A/D board. The current command was a sinusoidal function with variation in amplitude given by:

$$v(t) = 9.0 + 2.0\exp(-0.01t)\sin\left(\frac{2\pi t}{10}\right) \quad \text{[mA]} \qquad (24)$$

This sinusoidal input provided sufficient travels in the hysteresis model and other subsystems such that vital information about the pneumatic system was obtained. After the data acquisition had been done, the parameter identification was performed by the GAASS method. Lastly, the identified system parameters were fed to the hysteresis inverse model, H^{-1}, developed by Tao and Kokotović in [2] to carry out the hysteresis inverse compensation. The flow diagram of the hysteresis inverse compensation is depicted in Fig. 3.

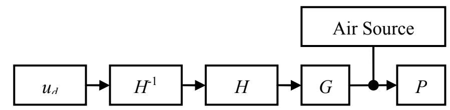

Fig. 3 Hysteresis inverse compensation

Using a population size N_{pop} = 10, generation number *gen* = 500, contraction rate c = 0.007, subspace coefficient ξ = 0.02, and search domains: $\tau \in [0, 20]$, $\zeta \in [0, 0.99]$, $\omega_n \in [0, 10]$, $m_b \in [0, 10]$, $c_{b,l} \in [-10, 10]$, $c_{b,r} \in [-10, 10]$, $m_{h,l} \in [0, 5]$, $m_{h,r} \in [0, 5]$, $m_{h,t} \in [0, 5]$, $m_{h,b} \in [0, 5]$, $c_{h,l} \in [-5, 5]$, $c_{h,r} \in [-5, 5]$, $c_{h,t} \in [4, 20]$, $c_{h,b} \in [4, 20]$, the GAASS had been run for ten times using different random seeds. The identified parameter values were averaged after the ten runs and are shown in Table 1. Fig. 4 shows the comparison of the identified hysteresis using various sensor measurements. As seen from Fig. 4, the hystereses identified using different sensor measurements have matched well with the predefined hysteresis.

Sensor	τ	ζ	ω_n	m_b		$c_{b,l}$		$c_{b,r}$	
pos.	N/A	N/A	N/A	1.09		0.48		1.02	
pres.	1.79	N/A	N/A	1.11		0.59		1.15	
flow	N/A	0.51	0.22	1.10		0.55		1.09	
	$m_{h,l}$	$m_{h,r}$	$m_{h,t}$	$m_{h,b}$	$c_{h,l}$	$c_{h,r}$	$c_{h,t}$	$c_{h,b}$	$\%e_r$
pos.	1.01	1.08	0.08	0.12	-0.28	0.92	10.71	7.20	2.38
pres.	1.08	1.11	0.10	0.10	0.11	1.07	10.72	7.34	10.56
flow	1.01	1.09	0.10	0.13	-0.32	1.04	10.36	7.26	4.83

Table 1 Parameter values identified by GAASS

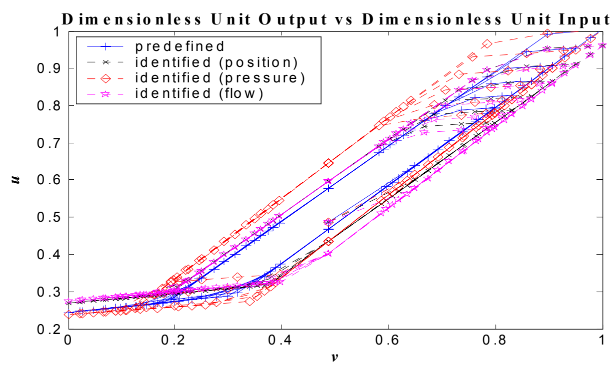

Fig. 4 Comparison of the identified hysteresis

Since the induced actuator hysteresis was static, the hysteresis inverse model derived from the successfully identified parameter values should be able to compensate the hysteresis effect of any type of control input. Thus, a sinusoidal function different from Eq. (24) was employed as the control input, u_d, given by:

$$u_d(t) = 9.0 + 1.0\sin\left(\frac{2\pi t}{12}\right) \quad \text{[mA]} \qquad (25)$$

Figs. 5 – 7 have revealed the effect of this hysteresis identification and inverse hysteresis compensation method when u_d was applied to control the actuator for a duration of 60 seconds and a sampling time of 0.5 second.

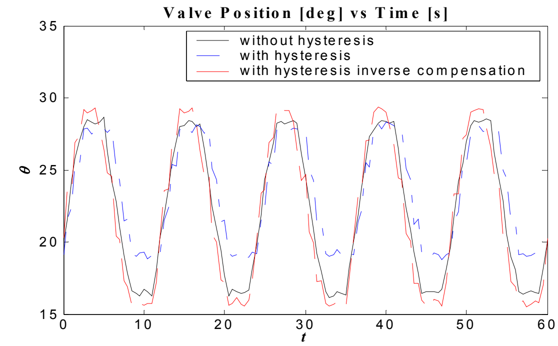

Fig. 5 Actuator position control performance

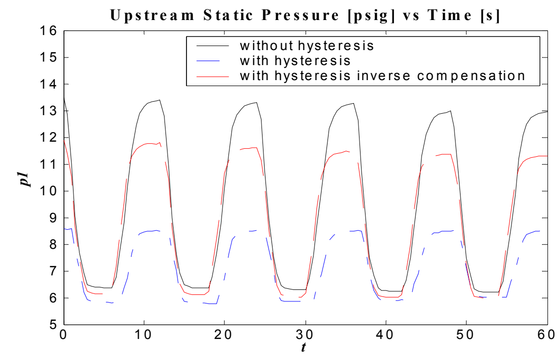

Fig. 6 Pressure control performance

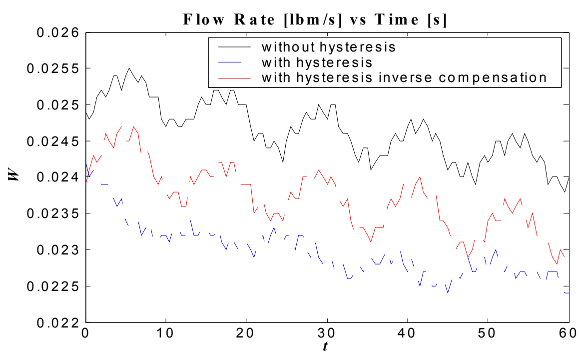

Fig. 7 Flow control performance

The effectiveness of the hysteresis inverse compensation was measured by the average percentage control error, $\%\varepsilon_c$, which calculates the difference between the output corresponds to the compensated signal, $w_{c,i}$ and the output corresponds to the control input signal, $w_{ud,i}$ over n number of data during the control period. $\%\varepsilon_c$ is given by:

$$\%\varepsilon_C = \sqrt{\sum_{i=1}^{n} \left| w_{c,i} - w_{u_d,i} \right|^2 \Big/ \sum_{i=1}^{n} \left| w_{u_d,i} \right|^2} \times 100\% \qquad (26)$$

The compensation results have shown that $\%\varepsilon_c = 3.80$ if the position sensor is used, $\%\varepsilon_c = 13.27$ if the pressure transducer is used, and $\%\varepsilon_c = 38.87$ if the thermal flow sensor is used.

5. CONCLUSIONS

The proposed GAASS approach has efficiently identified the hysteresis model parameters of an electromechanical-valve actuator. The hysteresis inverse model derived from the identified hysteresis parameters has effectively softened the effect of hysteresis. In fact, the method works extremely well in actuator position control with $\%\varepsilon_c$ of only 3.80. However, with the absence of pressure or flow regulation in the system, both the pressure and flow rate drop as time passes, which leads to the higher $\%\varepsilon_c$ of 13.27 and 38.87 in pressure control and the flow control, respectively. Nevertheless, with the use of the hysteresis inverse compensation, the pressure and flow control precisions have definitely improved as indicated by the amplitude recovery and the phase lag reduction.

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