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ACTUATOR HYSTERESIS MODELING AND COMPENSATION WITH AN ADAPTIVE SEARCH SPACE BASED GENETIC ALGORITHM

by

**CHE-HANG CLIFF CHAN, B. Eng. (AEROSPACE)
RYERSON UNIVERSITY, 2001**

A thesis
presented to Ryerson University
in partial fulfillment of the requirement for the degree of
Master of Applied Science
in the Program of
Mechanical Engineering

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ABSTRACT

Actuator Hysteresis Modeling and Compensation with An Adaptive Search Space Based Genetic Algorithm

© Che-Hang Cliff Chan, 2003

Master of Applied Science

in the Program of

Mechanical Engineering

Ryerson University

The thesis presents a *Genetic Algorithm with Adaptive Search Space* (GAASS) proposed to improve both convergence performance and solution accuracy of traditional Genetic Algorithms (GAs). The proposed GAASS incorporates an adaptive mechanism to control the size of the search space as well as the rates of crossover and mutation. The proposed GAASS method has been hybridized to a real-coded genetic algorithm to perform hysteresis parameters identification and hysteresis inverse compensation of an electromechanical-valve actuator installed on a pneumatic system. The experimental results have demonstrated the supreme performance of the proposed GAASS in the search of optimum solutions.

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NOMENCLATURE

Roman

c	contraction rate of the adaptive search space; zero-crossing of backlash and hysteresis models
c_d	valve discharge coefficient
e	expected value; error term associated with the measurement of system output and the difference between the actual output and the output generated from the system mapping model
f	fitness value
g	gravity constant $\equiv 386.4 \text{ in/s}^2$; inequality constraint
gen	maximum number of generations
m	total number of parameters; slope of backlash and hysteresis models
p	selection probability; pressure
p_c	crossover rate
p_m	mutation rate
r	random floating-point number
s	adaptive search space index
t	time
u	output signal
u_d	control command signal
v	input signal
W	mass flow rate
x	system parameter
y	system output
A	flow area
B	backlash
C	constraint
D	adaptive search domain
G	actuator
H	hysteresis

J	fitness (objective) function
N_c	total number of chromosomes (strings of parameters) undergoing crossover
N_m	total number of genes (individual parameters) undergoing mutation
N_{ipop}	initial population size
N_{pop}	population size
NFD	normalized fitness distance
P	plant
R	universal gas constant $\equiv 639.6 \text{ Btu}/^\circ\text{R}$
T	temperature
V	flow velocity; sensor voltage output
X	system parameter space
Y	system output space

Roman Script

$\mathcal{L}$	Laplace transform
---------------	-------------------

Greek

α	crossover site
γ	half search domain of the adaptive search space; isentropic coefficient of air $\cong 1.4$
δ	mutation site
ε	small positive number to prevent zero division
ε_c	control error
ζ	damping ratio
θ	valve-opening angle
λ	multipliers of the convex combination
μ	random floating-point number to replace the parameter at the selected mutation site; friction coefficient
ξ	subspace coefficient
ρ	air density

τ	flow time constant
χ	chromosome (string of parameters) chosen to perform mutation
ω_n	natural frequency
ψ	system mapping model
ω	adaptive search subspace
Ω	adaptive search space

Subscript

1	upstream of valve
2	downstream of valve
<i>amb</i>	ambient (atmospheric) condition
avg	average
<i>b</i>	backlash; bottom
<i>CV</i>	control valve (electromechanical-valve actuator)
<i>FB</i>	feedback control
<i>FS</i>	thermistor flow sensor
<i>h</i>	hysteresis
<i>l</i>	left-hand-side
<i>m</i>	measurement
max	maximum
min	minimum
<i>P</i>	position sensor (potentiometer)
<i>PS</i>	pressure transducer
<i>r</i>	right-hand-side
<i>t</i>	top
<i>vessel</i>	pressure vessel

Diacritic Symbol

·	rate of change
^	simulation model; identified parameter

CHAPTER 1 INTRODUCTION AND LITERATURE REVIEW

1.1 Motivations

Hysteresis is a type of nonlinearity caused by stiction, magnetism, or gears with backlash, and it often severely limits system performance by giving rise to tracking errors, limit cycles, undesired stick-slip motions, or even instability [43]. Hysteresis can be found in a variety of engineering applications such as piezoelectric actuators [18, 19], structures being stressed beyond their elastic limits [32, 45], friction force as a result of micro displacements [35, 38], and magnetic materials in the presence of alternating electromagnetic fields (ferromagnetic effect) [29, 43]. The success removal of hysteresis can dramatically reduce the operational and maintenance cost of a control system. Thus, control engineers often find ways to compensate the effect of hysteresis in systems. To counteract the hysteresis effect, precise hysteresis model is required in designing controllers with hysteresis compensation ability. Hence, the identification of hysteresis model and the implementation of hysteresis compensators have become a subject of increasing interests in recent years.

Conventional system identification methods that involve heuristic algorithms, such as the gradient-based least square approximation [17], the on-line recursive implementation of the least squares estimation [33], and the interacting multiple model (IMM) approach using the Kalman filter [38] all require derivative calculations of the objective function with respect to hysteresis parameters [32] and cannot be easily applied to non-differentiable, as well as highly non-linear and high-dimensional models [16]. On the other hand, stochastic algorithms such as Simulated Annealing (SA) [8, 16, 27, 28], Genetic Algorithms (GAs) [23, 26, 49], Evolutionary Programming (EP) [15, 49], Evolution Strategies (ESs) [41, 49], and their recombined algorithms, which do not require derivative calculations have provided good approximation solutions in the case of complicated multimodal, discontinuous, non-differentiable, and even noisy or moving response surface optimization problems in the past [16, 20, 21, 25]. The major advantage of these stochastic algorithms is their ability to identify parameters without any divergence in any case and therefore, have been most commonly used in a variety of searching and optimization problems.

Each of these stochastic algorithms has its advantage and disadvantage. SA is a powerful algorithm in high-order problem optimization, but is very slow [8, 27]. EP and ESs are very effective in multimodal function optimization, but both require heavy computation for the self-adaptation of control parameters. It is still unclear at this stage whether self-adaptation is beneficial to the convergence performance since the search space is increased exponentially [49]. Among the stochastic algorithms mentioned, GAs are perhaps the most widely used due to their high versatility and search performance [2, 4, 14, 20, 21, 22, 23, 37, 42]. However, the binary encoding in GAs consumes a huge memory when applied to engineering problems involving a large number of design variables. For the past decade, floating point representation of parameters as a chromosome (real-number encoding) is used more and more often because it uses much less memory than the binary encoding. Results have shown that real-coded GAs have demonstrated a superior performance as compared to the ones using binary encoding for both the smooth and highly oscillatory functions [13, 36, 37, 46].

The supreme versatility and performance of the real-coded GA has inspired the author to implement it onto the hysteresis parameters identification and compensation system that has the ability to outperform conventional methods. In order to improve the search efficiency, which is of superior importance for such applications, a *Genetic Algorithm with Adaptive Search Space* (GAASS) is proposed. The proposed GAASS is defined as a heuristic search method applied to GAs to improve their search performance.

In this thesis, a predefined hysteresis model is applied to simulate the hysteresis effect on an electromechanical ball-valve actuator that is installed on a pneumatic system. Since the parameters of the hysteresis model are known, we can validate the effectiveness of the proposed GAASS by comparing the discrepancies between the predefined and the identified hysteresis models. The thesis focuses on the single-processed actuator hysteresis identification and compensation. The hysteresis inverse model developed by G. Tao and P. V. Kokotović *et al.* is chosen here to perform the hysteresis compensation [43]. This feed-forward compensation provides a convenient way for the proposed hysteresis identification method to employ. To further demonstrate the versatility of this approach, the author has utilized three independent sensor measurement methods for the hysteresis identification procedure: position sensor (potentiometer) measurement,

pressure transducer measurement, and thermistor flow sensor measurement. The position sensor is connected to the actuator gear-train. The pressure transducer is installed upstream of the pneumatic pipeline system while the thermistor flow sensor is installed downstream of the pneumatic pipeline system. For each measurement method, the hysteresis identification and compensation using hysteresis inverse model are performed, and the results are compared with each other.

1.2 Background on Genetic Algorithms (GAs)

Genetic Algorithms (GAs) are search methods based on principles from Darwin's evolution theory [23, 26]. They are a subset of Evolutionary Algorithms (EAs) which are regarded as a *population-based* version of *generate-and-test* search [4, 49]. In general, any algorithm that has both population-based and generate-and-test search features can be defined as EAs. Evolution Strategies (ESs), Evolutionary Programming (EP), and Genetic Algorithms (GAs) are three of the most commonly used EAs. In recent years, a general term of evolutionary algorithms has been used by more and more researchers to include all three algorithms since they use almost the same computational framework.

Evolution Strategies (ESs) were first proposed by Rechenberg and Schwefel in 1965 as a numerical optimization technique. The original evolution strategy did not use populations. A population was introduced into evolution strategies later [49].

Evolutionary Programming (EP) was first proposed by Fogel *et al.* in mid 1960's as one way to achieve artificial intelligence. Several examples of evolving finite state machines were demonstrated [49]. Since late 1980's, evolutionary programming was also applied to various combinatorial and numerical optimization problems.

Genetic Algorithms (GAs) was first proposed by Holland [26] and his students in 1975 although some of the ideas appeared as early as 1957 in the context of simulating genetic systems [49]. Genetic algorithms were first proposed as adaptive search algorithms, although they have mostly been used as a global optimization algorithm for either combinatorial or numerical problems. They are probably the most well-known branch of evolutionary algorithm.

Evolutionary Algorithms use search operators like recombination (crossover) and mutation to *generate* new solutions, and use selection to *test* which solutions are fitter than others in a *population* of potential solutions.

Recombination or crossover is an operator that controls the exchange of information between two (two-point recombination) or more (multi-point recombination) solutions which have been encoded to strings of parameters. In GAs, each parameter is encoded to binary-numbers to form *genes* and the strings of parameters are thus usually referred to as *chromosomes*. The recombination or crossover process can be thought of as the interpolation and/or extrapolation of solutions. The term “crossover” is usually applied to binary-coded GAs because of their genetic representation (*genotype*) of parameters. For other evolutionary algorithms that use real-number encoding, “recombination” is used instead because they do not have a genotype and their parameters are encoded into the solution space (*phenotype*). However, the term “crossover” can also be used to describe the exchange of information in real-number encoded GAs (real-coded GAs) or Gray-coded GAs.

Mutation is an operator that controls the diversity of a population. Its role varies in different EAs [10]. In general, it performs population diversification by randomly altering values of parameters (*genes*) in strings of parameters (*chromosomes*).

Selection is an operator that mimics Darwin’s evolution theory. It selects individual chromosome to survive according to its fitness in the population.

Recent methods have been developed to enhance the robustness of GAs and EAs such as, hybrid method using *local optimizer* [20, 48], *Adaptive Range Genetic Algorithms* (ARGAs) [3], and *migration* [20, 21]. These methods have the advantage of finding better solutions over the conventional EAs. However, they all have the disadvantage of high computation complexity. The proposed *Genetic Algorithm with Adaptive Search Space* (GAASS) here provides an accurate search while having low complexity. Hence, it is applied to this application of actuator hysteresis identification.

To demonstrate the effectiveness of the proposed method, GAASS is implemented to two types of genetic algorithms: real-coded genetic algorithms (GAs) [24, 25] and real-coded Micro-Genetic Algorithms (Micro-GAs) [5, 30], and their

convergence performances are compared with those obtained using the traditional real-coded GAs, real-coded Micro-GAs and two other recently developed heuristic search techniques used in Adaptive Range Genetic Algorithm (ARGA) and Hybrid Genetic Algorithm Using Local Optimizer Based on Heuristic Pattern Move (*hGA*) [48]. Their convergence performances are compared through the solving of three high-multimodal and high-dimensional functions shown in Section 2.2.

1.3 Background on Actuator Hysteresis

Hysteresis is defined as a nonlinearity in which two output values are obtained for the same input value, one while the input is increasing and the other while the input is decreasing. The notation of hysteresis is equated with the notation of “memory effect” nonlinearity [14, 31, 33, 43]. This means that the output signal of a system with hysteresis depends not only on the present value of the input signal but also on the order of their past input amplitudes. In general, hysteresis models can be classified into two categories according to Mayergoyz *et al.* [35]: 1) hysteresis with local memories, and 2) hysteresis with nonlocal memories. For the case of hysteresis with local memory, the future output path depends uniquely upon the future input for any given current output. In other words, the future path always follows the pattern of the major hysteresis loop (Fig. 1.1). For the case of hysteresis with nonlocal memory, future output depends not only upon the current output and future input but also on the past history of input extremum values. In other words, the future path does not always follow the pattern of the major hysteresis loop, but it follows the path of some minor loops between certain consecutive extrema of the past input (Fig. 1.2).

Fig. 1.1: Hysteresis with local memory

Fig. 1.2: Hysteresis with nonlocal memory

Hysteresis can be further classified into the static and dynamic type [31, 33, 35]. Static hysteresis is rate-independent while dynamic hysteresis is rate-dependent. The term “rate” implies to the change of speed of the input signal. The output signal of a system with static hysteresis always demonstrates a looping behaviour when the input is varied back and forth between two consecutive extrema (Fig. 1.3). However, the output signal of a system with dynamic hysteresis does not follow a looping behaviour but a branching behaviour most of the time (Fig. 1.4). Most real-world hystereses belong to the dynamic type with nonlocal memory.

Fig. 1.3: Static hysteresis

Fig. 1.4: Dynamic hysteresis

Over the last 65 years, hysteresis models with nonlocal memories have been developed in many different ways. The Bouc-Wen model [47], the Chua-Stromsmoe model [7], and the Preisach model [39] are some of the most commonly used hysteresis models. Bouc-Wen model is the hysteresis model of Bouc modified by Wen which possesses an appealing simplicity, and is able to represent a large class of hysteretic behaviour, from stress-strain relationships in inelastic structures to magnetorheological behaviour [35]. Chua-Stromsmoe model is used to model ferromagnetic hysteretic inductors, and it allows extensive control over frequency-dependent behaviour, such as loop widening or narrowing for different frequency ranges. Among them, the Preisach model is the best-known hysteresis model. The Preisach model was developed by P. Preisach in 1938. It was originally used to describe hysteretic nonlinearity in ferromagnetism. It is now used to describe many physical phenomena with hysteretic behaviour, such as piezoceramic actuator hysteresis [17, 18, 19, 31], magnetostrictive actuator hysteresis [45], and pseudoelastic crystal hysteresis [16], etc.

All of the mentioned models, however, are limited to linear or differentiable nonlinear systems and are not suitable for adaptive and inverse controls. Therefore, a simplified hysteresis model, *Krasnosel'skii's hysteron* [29], which captures most of the hysteresis characteristics and is capable for parameter inverse compensation is employed in this thesis. Krasnosel'skii's hysteron was developed by Krasnosel'skii and Pokrovskii in the 1970s. It was derived from the Preisach model and was posited as a universal hysteresis representation for a vast variety of applications [29, 43]. The hysteron is a piecewise, linear description of hysteresis loops with nonlocal-memory. A typical actuator hysteresis modeled by Krasnosel'skii's hysteron is shown in Fig. 1.5.

Fig. 1.5: Actuator hysteresis modeled by Krasnosel'skii's hysteron

1.4 Background on System Identification and System Inverse Compensation

System identification is generally defined as identifying the parameter set of an input-output mapping model when the input and output signals are known. System identification can be divided into two categories: parametric and non-parametric. Parametric system identification implies to the determination of parameter values for an assumed mapping model and aims to identify their parameter values from experimental records. Non-parametric system identification, on the other hand, determines parameter values by producing the best functional representation for the mapping model without a priori assumptions about its physical nature.

In system identification, the most common way to identify the parameters of the unknown system is curve fitting [6, 33, 34], but it has a drawback of being an off-line process if the tuning algorithm is slow. For the GAASS method, since its computation time is short, it is capable for the on-line purpose. The objective of this method is to minimize the error between the actual and the simulated outputs through the continuous adaptation of the system parameters in the mapping model until the error falls below a predefined limit or the tuning algorithm reaches its maximum iteration (stop criterion). The curve fitting method has the advantage of averaging out the effects of measurement error, especially at high frequencies. However, the disadvantage of this method is the inability to estimate time-dependent parameters. In other words, the unknown system can only be identified as static within a certain data acquisition period. The structure of the system parameters identification using the curve fitting method is illustrated in Fig. 1.6.

Fig. 1.6: General structure of a system parameters identification using the curve fitting method

System inverse compensation is a type of model-based, feed-forward compensation. Previous works have been done using this inverse compensation for the control of piezoelectric actuators with hysteresis [31], plants with unknown hysteresees [43], and magnetostrictive transducers with hysteresis [45]. This control method provides the capability for effective design and implementation of robust control in an inexpensive manner. Suppose that the identified unknown system is an input (i.e. actuator) nonlinearity, $N(\cdot)$, then a nonlinearity inverse compensator, $N^{-1}(\cdot)$, can be placed before $N(\cdot)$ to carry out the feed-forward compensation. Fig. 1.7 has illustrated the flow diagram of the system inverse compensation. The control input, input signal to the input nonlinearity, output signal from the input nonlinearity, and the actual plant output are denoted by u_d , v , u , and y respectively.

a) Plant with input nonlinearity $N(\cdot)$

b) Inverse compensator $N^{-1}(\cdot)$ for the input nonlinearity $N(\cdot)$

Fig. 1.7: General structure of the system inverse compensation

In system identification and system inverse compensation, the input/output data are first acquired within a certain data acquisition period. Then, the identification of the system parameters is performed. Lastly, the identified system parameters are fed into an inverse model to perform the system inverse compensation. The procedure of the system identification and system inverse compensation is illustrated in Fig. 1.8.

Fig. 1.8: Flow diagram of the system identification and system inverse compensation

In this thesis, both the parametric and non-parametric system identifications are employed. Parametric system identification is applied to identify the parameters of the actuation backlash and the predefined actuator hysteresis that induced to the actuator. Non-parametric system identification is applied to identify the parameters of the duct

pressure dynamics and the thermistor flow sensor dynamics. The curve fitting method illustrated in Fig. 1.6 is used for both identification processes and is driven by the proposed GAASS method as the tuning algorithm.

1.5 Contributions of This Thesis

There are three major contributions in this thesis:

- I. A new heuristic search technique, the GAASS is developed and hybridized to GAs to improve their search performance.
- II. The proposed GAASS is implemented successfully to both the simulation as well as the real application of the actuator hysteresis identification and its hysteresis inverse compensation.
- III. Pressure transducer and thermistor flow sensor are utilized successfully in the hysteresis identification procedure.

1.6 Organization of This Thesis

The thesis is organized in two major parts. The first part focuses on the discussion of the GAASS and its search performance while the second part focuses on the discussion of the actuator hysteresis identification and the actuator hysteresis inverse compensation. This thesis is presented as follows: Chapter 2 defines the proposed GAASS method and demonstrates its robustness through the comparison of results obtained by some test functions solved using various GAs; Chapter 3 describes the hysteresis parameters identification using the GAASS method and the hysteresis compensation using the hysteresis inverse model; Chapter 4 provides the simulation results of the hysteresis parameters identification and the hysteresis inverse compensation; Chapter 5 provides the experimental results of the hysteresis parameters identification and the hysteresis inverse compensation; and Chapter 6 draws some conclusions and proposes further directions of future research.

CHAPTER 2 GENETIC ALGORITHM WITH ADAPTIVE SEARCH SPACE (GAASS)

2.1 Structure of GAASS

The proposed *Genetic Algorithm with Adaptive Search Space* (GAASS) incorporates an adaptive mechanism in defining the search space in traditional genetic algorithms (GAs). It is a *heuristic* search method that hybridized into the real-coded GA and it bridges the gap between *stochastic search* and *heuristic search*. In general, search can be performed with either stochastic search or heuristic search. Stochastic search does not use additional information about the problem domain in the search of solutions (blind search) while heuristic search uses additional information such as gradients calculation to guide the search along with the best search directions. These two search methods demonstrate two unique search strategies: *exploration* and *exploitation* [10, 20]. Stochastic search performs search space exploration while ignoring the exploitation of the promising regions of the search space (random search being the extreme case). Heuristic search performs exploitation of the best solution for possible improvement while ignoring the exploration of the search space (gradient-based algorithms being the extreme case). It has been proven that the maintaining of a good balance between exploration and exploitation is essential as many researchers state that the effectiveness of search methods depend upon the appropriate mix of exploration and exploitation [9, 10, 11, 12, 44]. Tradition GAs have a good balance between exploration and exploitation of the search space. However, many of them, especially the Simple Genetic Algorithm (SGA) [23] have very little power in exploiting the best solution. The GAASS method adds a degree of exploitation power in traditional GAs, which helps perform better local exploitation around chromosomes and are able to maintain a good balance between exploration and exploitation in the search space.

The GAASS method is hybridized into two types of GAs, traditional GAs and Micro-GAs, so to demonstrate its effectiveness in the GAs family. Traditional GAs and Micro-GAs are very similar in terms of computational structure except that their population size and the mechanism to introduce and maintain the genetic diversity are different [30]. Micro-GAs refer to as small-population genetic algorithms with

reinitialization. The population size of Micro-GAs usually ranges from 5 to 10. GAs in general have five operators in their computational framework: *initialization*, *evaluation*, *selection*, *crossover (recombination)*, and *mutation* [14, 15, 20, 23, 24, 26]. The genetic operators, crossover and mutation are used for the search space *exploration* and the genetic *diversification* of a population. In Micro-GAs, however, *reinitialization* is added to the five operators in maintaining the genetic diversity of a population [1, 30, 36]. The major advantage of Micro-GAs over GAs is their fast convergence speed, but their solution consistency is not guaranteed to be better than that of GAs. Fig. 2.1 illustrates the differences in computational structures of GAs and Micro-GAs.

Fig. 2.1: Flow charts of GAs and Micro-GAs

The structure of the GAASS is similar to the traditional GAs, which consists of five major operators: initialization, evaluation, selection, crossover (recombination), and mutation. Except for initialization, which only performs once in the entire procedure, all other four operators execute in every generation until the predefined maximum number of generations, *gen*, is reached (stop criterion). The following sections describe the

operators of the GAASS including the initialization method, adaptive search space method, selection scheme, and the adaptive crossover and mutation techniques.

2.1.1 Initialization

The initial real-number chromosomes are randomly generated from within the feasible region (constraint) of each parameter x in this operator. The *rejecting strategy* [20] is employed here to handle the constraints of the parameters. Rejecting strategy discards all infeasible chromosomes created throughout the evolutionary process. Thus, only the (feasible) chromosomes fall within the parameter constraints are generated in initialization. The initial population (sampling) size N_{ipop} is set to twice the size of the population in the latter generations N_{pop} in GAASS. 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 search space [25]. The pseudo code of the initialization subroutine is described in Fig. 2.2.

Fig. 2.2: Pseudo code of the initialization subroutine

2.1.2 Evaluation

The evaluations 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 that is to be optimized by GAASS. The fitness function of our identification system is given in Eq. (3.6).

Selection probability p_k and 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 , p_k and e_k are given by

$$p_k = f_k / \sum_{i=1}^{N_{pop}} f_i \quad (2.1)$$

$$e_k = N_{pop} \times p_k \quad (2.2)$$

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

$$NFD = \begin{cases} \frac{(f_{max} - \bar{f} - \varepsilon)}{(f_{max} - f_{min} + \varepsilon)} & \text{for minimization problem} \\ \frac{(\bar{f} - f_{min} - \varepsilon)}{(f_{max} - f_{min} + \varepsilon)} & \text{for maximization problem} \end{cases} \quad (2.3)$$

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. For minimization problem, values of $\bar{f}$ and f_{min} will approach the value of f_{max} as generation progresses. For maximization problem, values of $\bar{f}$ and f_{max} will approach the value of f_{min} as generation progresses. Thus, the value of *NFD* will gradually decrease as the solution approaches the optimum value.

By comparing the normalized fitness distance (*NFD*) of the present population with that of the previous population, the GAASS determines the appropriate search space for the next generation. If the *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*, Ω , will be reduced. Otherwise (solution diverges), it will remain the same as that in the previous generation. When the solution converges, Ω contracts so to increase the pressure of search space exploitation in order to perform better local optimization among

chromosomes. However, when the solution diverges, Ω remains unchanged so to increase the pressure of search space exploration by allowing more degrees of freedom. In doing so, new genetic materials are introduced which can hopefully produce better chromosomes in the latter generations. Besides the size of Ω , the origin of Ω also changes adaptively according to the average of each parameter $\bar{x}_i$ in the current population given by

$$\bar{x}_i = \frac{\sum_{k=1}^{N_{pop}} x_{i,k}}{N_{pop}} \quad \forall i \in \{1, \dots, m\} \quad (2.4)$$

where m denotes the number of parameters. Hence, the adaptive search space $\Omega \in \mathbb{R}^m$ is expressed as

$$\begin{aligned} \Omega &= \prod_{i=1}^m [\max\{C_{lower,i}, D_{lower,i}\}, \min\{C_{upper,i}, D_{upper,i}\}] \\ &= \prod_{i=1}^m [\max\{C_{lower,i}, (\bar{x}_i - \gamma_i)\}, \min\{C_{upper,i}, (\bar{x}_i + \gamma_i)\}] \end{aligned} \quad (2.5)$$

where γ is the half search domain, C_{lower} and C_{upper} are the lower and upper bounds of the parameter constraints, and D_{lower} and D_{upper} are the lower and upper bounds of the adaptive search domains. The half search domain γ starts with half of the parameter constraint $\gamma_{i,init}$, then it is reduced dynamically according to the exponential function defined by

$$\gamma_i(j) = \gamma_{i,init} \exp(-cs) \quad \forall i \in \{1, \dots, m\}, j \in \{1, \dots, gen\} \quad (2.6)$$

where c is a positive, problem-dependent coefficient which controls the contraction rate of the adaptive search space and s is the adaptive search space index given by

$$s = \begin{cases} 1 & \text{if } j = 1 \\ s+1 & \text{if } NFD(j) \leq NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \\ s & \text{if } NFD(j) > NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \end{cases} \quad (2.7)$$

The adaptive search space provides the appropriate search region for the regeneration of chromosomes and the mutation of genes to take place. Eq. (2.5) – (2.7) define the location and size of the adaptive search space Ω . The origin of Ω is determined by the average of each parameter $\bar{x}_i$ given in Eq. (2.4). The size of Ω is determined by the half search domain γ according to Eq. (2.5), which states that if the

lower bound of the adaptive search domain D_{lower} falls outside the range of the parameter constraint, it will be replaced by the lower bound of the parameter constraint C_{lower} . This is also true for D_{upper} , where it will be replaced by the upper bound of the parameter constraint C_{upper} . The contraction rate of the adaptive search space described in Eq. (2.6) and Eq. (2.7) is a rather *deterministic adaptation* [21] approach since the coefficient c can be of any arbitrary positive value and the contraction expression can be defined according to the user's judgement. A general rule to the adaptive search space contraction is that the majority of the good chromosomes should converge inside the contracted search space. Otherwise, some vital information about the good chromosomes will be discarded unintentionally. The pseudo code of the evaluation subroutine is described in Fig. 2.3.

Fig. 2.3: Pseudo code of the evaluation subroutine

2.1.3 Selection

Selection is performed using the *remainder stochastic sampling* [20, 34]. This *mixed sampling* approach contains both stochastic and deterministic features simultaneously, and it has outperformed other selection schemes [34]. To further improve the convergence performance, the *elitist selection* [5, 20, 34, 48] scheme is also used to ensure that the best chromosome is always taken to the next generation. Tournament selection performs selection in the first generation and in the latter generations, remainder stochastic sampling selects and reproduces the better chromosomes in the population according to their expected values. The pseudo code of the selection subroutine is described in Fig. 2.4.

Fig. 2.4: Pseudo code of the selection subroutine

2.1.4 Crossover (recombination)

Crossover is the main search operator in GAs which performs the exchange of information among chromosomes through combination and disruption of schemata [10, 20, 23]. Combination of schemata refers to the generation of linear combination of parent chromosomes while disruption of schemata means the ability to introduce new materials in a population. Investigations in for instance [9, 10, 11], 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.

As in traditional GAs, the number of mating takes place in a population depends on the crossover rate, p_c , which is usually a fixed value. However, in GAASS, p_c is changed adaptively according to the normalized fitness distance NFD . If the 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 follows

$$p_c = \begin{cases} p_{c,h} & \text{if } NFD(j) \leq NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \\ p_{c,l} & \text{if } NFD(j) > NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \end{cases} \quad (2.8)$$

where the values of $p_{c,l}$ and $p_{c,h}$ are set to 0.5 and 0.9, respectively. According to Eq. (2.8), the number of offspring that will be generated in a population N_c , is given by

$$N_c = N_{pop} \times p_c \quad (2.9)$$

The maximum number of offspring that can be generated in a population is equal 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 Ω to fill the vacancy according to the following equation

$$x_{k,i}(j) = \bar{x}_i(j) + r(\gamma_i(j)) \quad \forall i \in \{1, \dots, m\}, j \in \{1, \dots, gen\}, k \in \{(N_c + 1), \dots, N_{pop}\} \quad (2.10)$$

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 the adaptive search space Ω such that some new 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 Ω is relatively large and the Euclidean distance between the global optimum and the origin of Ω is relatively long, regeneration performs a more stochastic search in Ω , which hopefully provides better chromosomes for the latter generations. Second, during latter generations where the size of Ω is relatively small and the Euclidean distance between the global optimum and the origin of Ω is relatively short, regeneration performs a more heuristic search in Ω , which helps exploiting the better solution.

In GAASS, crossover executes from the second generation on until the number of generations reaches the predefined maximum number (*gen*). The crossover operator employs the two-parent crossover scheme. This crossover scheme allows two randomly selected parents to mate at a time and generate two offspring within the feasible region bounded by the parameter constraints. If the two selected chromosomes are identical, this chromosome will be reproduced itself to form the first offspring, and the second offspring will be generated randomly from the feasible region. The crossover procedure is performed by the combination of *arithmetic crossover* and *schema processing* in binary GAs [13, 21, 40]. This method is a combination of an interpolation method with a crossover method, which closely mimics the advantages of the binary GA mating scheme [24, 25, 40]. Suppose that the k^{th} and $(k + 1)^{\text{th}}$ chromosomes are selected as parents in a population

$$\begin{aligned} \text{parent}_k &= [x_{k,1} x_{k,2} \dots x_{k,\alpha} \dots x_{k,m}] \\ \text{parent}_{k+1} &= [x_{k+1,1} x_{k+1,2} \dots x_{k+1,\alpha} \dots x_{k+1,m}] \end{aligned}$$

the combined crossover method begins by randomly selecting a parameter site, $\alpha \in [1, m]$ in the two parents to be the crossover point. Then, the selected parameter are combined to form the new parameters in the offspring according to the *convex combination* [21] of the arithmetic crossover method given by

$$\begin{aligned} x'_{k,\alpha} &= \lambda_1 x_{k,\alpha} + \lambda_2 x_{k+1,\alpha} \\ x'_{k+1,\alpha} &= \lambda_1 x_{k+1,\alpha} + \lambda_2 x_{k,\alpha} \end{aligned} \tag{2.11}$$

where the multipliers λ_1 and λ_2 are restricted to

$$\lambda_1 + \lambda_2 = 1, \quad \lambda_1 > 0, \quad \lambda_2 > 0 \quad (2.12)$$

The final step of the mixed crossover method is to complete the schema processing by swapping the parameters to the right of the crossover point. If the last parameters of the parent chromosomes are selected to be the crossover point, then only the parameters to the left of the crossover point are swapped. Hence, the offspring produced by the k^{th} and $(k + 1)^{\text{th}}$ parents in a population are generated as follows

$$\begin{aligned} \text{offspring}_k &= [x_{k,1}x_{k,2} \dots x'_{k,\alpha} \dots x_{k+1,m}] \\ \text{offspring}_{k+1} &= [x_{k+1,1}x_{k+1,2} \dots x'_{k+1,\alpha} \dots x_{k,m}] \end{aligned}$$

The newly formed parameters in the offspring are then examined by the parameter constraints to ensure that all parameters fall within the feasible region of the search space.

The pseudo code of the crossover subroutine is described in Fig. 2.5.

Fig. 2.5: Pseudo code of the crossover (recombination) subroutine

2.1.5 Mutation

Mutation is most commonly served as a background operator to restore genetic materials in GAs [10, 20, 23]. However, in GAASS, it functions as a background operator as well as a local optimizer since it is a guided-search operator controlled by Ω . Mutation rate is significant in the controlling of the GAASS performance because it induces diversity to a population and also exploits the better solution. If the mutation rate, p_m , defined as the number of parameters chosen to mutate in a population, is too high, good chromosomes will be distorted. If p_m is too low, GA will have a higher tendency to converge to a local optimum. In GAASS, the mutation rate p_m is changed adaptively according to the normalized fitness distance, NFD . If the NFD of the present population is smaller than or equal to that of the previous population, p_m is set to a higher value, $p_{m,h}$. Otherwise, p_m is set to a lower value, $p_{m,l}$. This adaptive mutation scheme ensures that chromosomes at any time have enough diversity for the GAASS to prevent premature convergence. When the solution converges, the mutation rate is increased so to increase the diversity of chromosomes in the next generation. On the other hand, when the solution diverges, the mutation rate is decreased since the population already has enough diversity. The adaptive mutation rate scheme is described as follows

$$p_m = \begin{cases} p_{m,h} & \text{if } NFD(j) \leq NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \\ p_{m,l} & \text{if } NFD(j) > NFD(j-1) \quad \forall j \in \{1, \dots, gen\} \end{cases} \quad (2.13)$$

where the values of $p_{m,l}$ and $p_{m,h}$ are set between 0.01 to 0.05 and between 0.1 to 0.5, respectively, depending on the population size and the number of parameters. According to Eq. (2.13), the number of mutations that will be performed in a population N_m , is given by

$$N_m = N_{pop} \times m \times p_m \quad (2.14)$$

where m denotes the number of parameters.

The mutation operator executes from the second generation on until the number of generations reaches the predefined maximum number (gen). Similar to the role of *regeneration*, mutation here performs a more stochastic exploitation in the subspace of the adaptive search space, ω , during early generations but it performs a more heuristic

exploitation in ω during latter generations. The subspace of the adaptive search space ω defines the range of local optimization and is given by

$$\omega = \xi\Omega \quad (2.15)$$

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

The mutation operator starts by randomly selecting a chromosome, $\chi \in [1, N_{pop}]$ from the population, then, a parameter from the selected chromosome is chosen as the mutation site, $\delta \in [1, m]$. Next, a random floating-point number in the subspace of the adaptive search space, $\mu \in \omega$ is generated to replace the parameter at the selected mutation site according to the following equation

$$x_{\chi,\delta}(j) = \bar{x}_{\delta}(j) + r(\xi\gamma_{\delta}(j)) \quad \forall j \in \{1, \dots, gen\} \quad (2.16)$$

where $r \in [-1, 1]$ is a random floating-point number. Suppose that the mutation site δ is chosen in chromosome χ as

$$chromosome_{\chi} = [x_{\chi,1} x_{\chi,2} \dots x_{\chi,\delta} \dots x_{\chi,m}]$$

then, after mutation, chromosome χ will become

$$chromosome_{\chi} = [x_{\chi,1} x_{\chi,2} \dots \mu_{\chi,\delta} \dots x_{\chi,m}]$$

The pseudo code of the mutation subroutine is described in Fig. 2.6.

Fig. 2.6: Pseudo code of the mutation subroutine

The GAASS uses the five operators discussed above to perform an effective search/optimization that contains both stochastic and heuristic characteristics. The mechanism of the adaptive search space method is performed together with the adaptive crossover and mutation techniques to control the pressures of search space exploration and search space exploitation. Fig. 2.7 demonstrates how the adaptive search space method functions in the feasible region of the search space, and Fig. 2.8 summarizes the complete procedure of the GAASS method.

Fig. 2.7: Mechanism of the adaptive search space method

Genetic Algorithm with Adaptive Search Space

Fig. 2.8: Flow chart of GAASS

To demonstrate the robustness of the proposed method, GAASS is compared with two other hybrid-GAs: Adaptive Range Genetic Algorithm (ARGA) and Hybrid Genetic Algorithm Using Local Optimizer Based on Heuristic Pattern Move (*hGA*). ARGA and *hGA* are two recently developed algorithms that hybridized heuristic search into the traditional real-coded GA and binary-coded GA to perform local exploitation.

The ARGA uses reinitialization to perform the local exploitation. The reinitialization operator, which restarts in every N (user-defined) generations, reproduces chromosomes around the average of each parameter according to the normal distribution. In doing so, more promising chromosomes are generated, hence, more accuracy solutions

can be found. However, the disadvantages of the ARGGA are that the computation of the normal distribution transformation is heavy and it requires high population size to make its probabilistic property significant. Fig. 2.9 illustrates the flow chart of the ARGGA.

Fig. 2.9: Flow chart of ARGGA

The *hGA* is a micro-GA which employs a local optimizer to perform the local exploitation around chromosomes. The local optimization process is implemented by replacing the two worst offspring obtained from the conventional genetic operators with two new individuals generated from the local optimizer in each generation. With the aid of the local optimizer, it is more effective and efficient to obtain the global optimum. The advantage of the *hGA* is its supreme convergence speed. However, its solution accuracy improvement is debatable since it cannot perform good search space exploitation in the early generations, and a good balance between exploration and exploitation cannot be maintained by just using a fix-rated local optimizer. The flow chart of the *hGA* is illustrated in Figure 2.10.

Fig. 2.10: Flow chart of *hGA*

The robustness of the GAASS is revealed by comparing its convergence performance with those of the traditional GA, Micro-GA, ARGA and *hGA*. The convergence performance of each of these algorithms is shown through the optimization of three multimodal test functions given in Section 2.2.

2.2 Convergence Performance of GAASS

The convergence performance of the GAASS is revealed by the optimization of the test functions performed separately by the traditional GA, Micro-GA, ARGAs and hGA. The three test functions, $F1$, $F2$, and $F3$ given by (2.15), (2.16), and (2.17) have been especially designed to have many local optima and one or more global optima for testing the performance of various GAs. These functions are selected from the examples used in the *Programme on Advanced Genetic Algorithm in Engineering School in Computer Science, Sophia Antipolis, France* [48].

$$F1: f(x_1, x_2) = \sum_{i=1}^5 i \cos[(i+1)x_1 + i] \sum_{i=1}^5 i \cos[(i+1)x_2 + i] \quad x_i \in [-10, 10] \forall i \in \{1, 2\} \quad (2.15)$$

Global optima = 186.7307 at $(x_1, x_2) = (5.4829, -1.4265), (4.8581, -7.0835),$
 $(-1.4251, -0.8003), (-0.8003, -1.4251),$
 $(-1.4251, 3.2800)$

$$F2: f(x_1, x_2, x_3, x_4) = \sum_{i=1}^5 \frac{1}{\sum [(x_j - d(i, j))^2] + c(i)}; \quad x_i \in [0, 1.0] \forall i \in \{1, 2, 3, 4\} \quad (2.16)$$

$$\text{where } d[5, 4] = \begin{bmatrix} 4 & 4 & 4 & 4 \\ 1 & 1 & 1 & 1 \\ 8 & 8 & 8 & 8 \\ 6 & 6 & 6 & 6 \\ 3 & 7 & 3 & 7 \end{bmatrix}; \quad c[5] = [0.1 \quad 0.2 \quad 0.2 \quad 0.4 \quad 0.4]$$

Global optimum = 10.1532 at $(x_1, x_2, x_3, x_4) = (4.0, 4.0, 4.0, 4.0)$

$$F3: f(x_1, \dots, x_{20}) = \sum_{i=1}^{20} [x_i^2 + 5(1 - \cos(\pi x_i))] \quad x_i \in [-3, 3] \forall i \in \{1, \dots, 20\} \quad (2.17)$$

Global optimum = 0 at $(x_1, \dots, x_{20}) = (0, \dots, 0)$

The test function $F1$, illustrated in Fig. 2.11, is a two-dimension multimodal function that has multiple global optima. The task of the GAASS is to identify any one of the global optima within the search domains. $F2$ and $F3$ are high-dimensional and high-oscillatory

functions that have only one global optimum. In fact, $F3$ has a total number of 2^{20} local optima and only one global optimum. Thus, the successful identification of these global optima can demonstrate the effectiveness of the proposed GAASS method. $F1$ and $F2$ have been solved using the micro-GA, hGA , and GAASS while $F3$ has been solved by the traditional GA, ARGA, and GAASS. The configurations of these algorithms used to optimize the three test functions are shown in Table 2.1. Tables 2.2 – 2.4 show the convergence results of these test functions using the GAASS. Each function has been run ten times using different random seeds. The comparisons of the convergence performance among other algorithms used are illustrated by the convergence plots in Fig. 2.12 – 2.14. These convergence plots show the convergence performance of the GAASS compared with the best convergence performance of the other GAs used in optimizing each of the three test functions.

Fig. 2.11: Graphical representation of $F1$

	GA	ARGA	micro-GA	hGA	GAASS		
$Nipop$	300	300	7	7	12	12	40
$Npop$	300	300	7	7	6	6	20
Max #generations (gen)	150	150	500	500	100	400	1000
Max #evaluations	45000	45000	3500	3500	606	2406	20020
pc,l	0.7	0.7	0.5	0.5	0.5	0.5	0.5
pc,h	0.7	0.7	0.5	0.5	0.9	0.9	0.9
pm,l	0.1	0.1	0	0	0.05	0.05	0.01
pm,h	0.1	0.1	0	0	0.5	0.5	0.1
Ω contraction rate (c)	N/A	N/A	N/A	N/A	0.046	0.011	0.0046
Ω subspace coefficient (ξ)	N/A	N/A	N/A	N/A	0.02	0.05	0.05
Function Solving	$F3$	$F3$	$F1, F2$	$F1, F2$	$F1$	$F2$	$F3$

Table 2.1: Configurations of the traditional GA, micro-GA, ARGA, hGA , and GAASS in solving the test functions $F1$, $F2$, and $F3$

Convergence Results for <i>F1</i> using GAASS										
Random Seed#	0	1	2	3	4	5	6	7	8	9
Fitness Value	183.76	186.36	186.71	185.51	184.29	182.21	182.32	186.68	186.01	184.75

Table 2.2: Convergence result for *F1* using GAASS

Convergence Results for <i>F2</i> using GAASS										
Random Seed#	0	1	2	3	4	5	6	7	8	9
Fitness Value	10.15	10.15	10.13	10.15	10.15	5.10	10.15	10.15	5.06	10.15

Table 2.3: Convergence result for *F2* using GAASS

Convergence Results for <i>F3</i> using GAASS										
Random Seed#	0	1	2	3	4	5	6	7	8	9
Fitness Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2.4: Convergence result for *F3* using GAASS

Fig. 2.12: Comparison of convergence for *F1*

Fig. 2.13: Comparison of convergence for $F2$

Fig. 2.14: Comparison of convergence for $F3$

As seen from the convergence results comparison, the proposed GAASS method clearly has the best convergence performance and solution accuracy compared to the other GAs. Its ability to handle high-dimensional and high-oscillatory functions has been confirmed by the successful optimization of the test functions, $F1$, $F2$, and $F3$. Hence, the GAASS method can virtually be applied to any engineering problems which have less or equal complexity to the three test functions. In general, there are three major advantages when applying the GAASS to optimization problems:

- I. The GAASS maintains the balance of exploration and exploitation throughout the entire generations so to improve the solution accuracy. Exploration is performed by the crossover (recombination) of chromosomes inside and outside of the adaptive search space region while exploitation is performed by selection, regeneration of chromosomes and mutation of genes inside the adaptive search space region. The two genetic operators, crossover and mutation are executed simultaneously in every generation and their rates of execution are controlled according to the *normalized fitness distance (NFD)* of the population.
- II. The GAASS does not require the extra computation of derivatives and statistical calculations. It has a low computation complexity of $O(N)$. Therefore, its computation speed is very fast.
- III. The GAASS can be implemented to GAs of any population size because the population size is not restricted to fulfill the characteristics of normal distribution.

CHAPTER 3 MODELING OF THE HYSTERESIS PARAMETERS IDENTIFICATION AND HYSTERESIS INVERSE COMPENSATION

3.1 Formulation of The Actuator Hysteresis Parameters Identification Using GAASS

System parameters identification is defined as identifying the parameter set $x \in X$ when the system output $y \in Y$ and the direct mapping $\psi: X \rightarrow Y$ are known [16, 25, 34]. The parameter space is given by

$$X = \{x \in X_1 \times \dots \times X_m \mid g_i(x) \geq 0, \forall i \in \{1, \dots, m\}\} \quad (3.1)$$

where $g_i(x): X_1 \times \dots \times X_m \rightarrow \mathbb{R}$ represents the inequality constraints. Mapping X to Y , the input-output relation can be expressed as

$$y = \psi(x) + e \quad (3.2)$$

where e represents the error term associated with the measurement error of y and the difference between the output y and the output generated from the mapping function $\psi(x)$. The objective of the system parameters identification is to minimize e in order to achieve the direct mapping $\psi: X \rightarrow Y$ until the desirable solution of the parameter set $x \in X$ is identified.

The system parameters identification employed in the thesis is a curve fitting approach that uses the proposed GAASS method as the tuning algorithm. Through the continuous adaptation of the parameters, the GAASS minimizes the sum of the squares error of e , represented by J as

$$J = \sum_{i=1}^n |e_i|^2 = \sum_{i=1}^n |y_i - \psi(x_i)|^2 \quad (3.3)$$

where J is defined as the fitness function of GAASS and n is the total number of data points. The objective of this method is to search for a set of parameter values $x \in X$ that will lead to a smaller J until the maximum generation of GAASS is reached and/or the relative percentage error, $\%e_r$, given by

$$\%e_r = \sqrt{J / \sum_{i=1}^n |y_i|^2} \times 100\% \quad (3.4)$$

falls below a predefined error bound (stop criterion). The general structure of the GAASS method employed in the thesis is illustrated in Fig. 3.1.

Fig. 3.1: General structure of a system identification using the GAASS method

In Fig. 3.1, input (v) represents the actuator current command; plant (P) represents the pneumatic pipeline system; actuator (G) represents the electromechanical-valve actuator installed in the pipeline; induced hysteresis (H) represents the predefined hysteresis model induced to the actuator; ψ represents the mapping model of the entire system which consists of the mathematical representations of actuator ($\hat{G}$), actuator hysteresis ($\hat{H}$), and plant ($\hat{P}$); and the fitness function (J) represents the evaluation process of the GAASS method.

In the GAASS method, the input v is passed onto two separate paths. One path goes to the real system while the other path goes to the system mapping model ψ . The real system produces the actual output which is measured by a position sensor, a pressure transducer, and a thermistor flow sensor in the pneumatic system while the system mapping model produces the simulated output which is calculated by $\hat{H}$, $\hat{G}$, and $\hat{P}$. The fitness function J given in Eq. (3.3) calculates the sum of the squares error between the actual output and the simulated output which provides as a feedback to the GAASS. The

GAASS method continuously searches for the best parameter values $x \in X$ in ψ such that the sum of the squares error J approaches a minimum until the stop criterion is met.

In this thesis, the GAASS method is applied to two types of system identification: parametric system identification and non-parametric system identification.

Parametric system identification is employed here to determine the parameters of the induced hysteresis model and the parameters of the actuation backlash. Non-parametric system identification is employed to determine the duct pressure dynamics and the thermistor flow sensor dynamics associated with the plant output without a priori assumptions about their physical nature. The following subsections describe the various parts in ψ that are used to construct the GAASS in the actuator hysteresis parameters identification.

3.1.1 Hysteresis Model

The hysteresis model represents the ferromagnetic effect occurs in the electromechanical-valve actuator. Krasnosel'skii's hysteron, which is suitable for system inverse control, is used here. The hysteron is a general piecewise, linear description of hysteresis loops with nonlocal-memory. G. Tao and P. V. Kokotović *et al.* have put together sets of equations to describe Krasnosel'skii's hysteron, denoted by the function $H(v(t)) \equiv H(m_{h,l}, m_{h,r}, m_{h,t}, m_{h,b}, c_{h,l}, c_{h,r}, c_{h,t}, c_{h,b}; v(t))$ [29, 43]. The graphical description of Krasnosel'skii's hysteron is depicted in Fig. 3.1.

Fig. 3.1: Graphical description of Krasnosel'skii's hysteron

The eight parameters in the function $H(v(t))$ represent four slopes $m_{h,l}$, $m_{h,r}$, $m_{h,t}$, $m_{h,b}$ and four crossings $c_{h,l}$, $c_{h,r}$, $c_{h,t}$, $c_{h,b}$, where the subscripts h,l , h,r , h,t , h,b indicate left, right, top, and bottom sides of the hysteresis loop respectively.

According to Tao and Kokotović's *et al.* description, the input $v(t)$ and output $u(t)$ of the hysteron are confined to two half-lines, two line segments, and the quadrilateral formed by those half-lines and segments. The half-lines are described by

$$u(t) = m_{h,l}v(t) + c_{h,l}, v(t) > v_1 = \frac{c_{h,t} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,t}} \quad (3.5)$$

$$u(t) = m_{h,b}v(t) + c_{h,b}, v(t) < v_2 = \frac{c_{h,b} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,b}} \quad (3.6)$$

and the line segments are

$$u(t) = m_{h,r}(v(t) - c_{h,r}), v_2 \leq v(t) < v_3 = \frac{c_{h,t} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,l}} \quad (3.7)$$

$$u(t) = m_{h,l}(v(t) - c_{h,l}), \frac{c_{h,b} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,b}} = v_4 < v(t) \leq v_1 \quad (3.8)$$

where v_1 , v_2 , v_3 , and v_4 are the values of $v(t)$ at the upper-left, lower-right, upper-right, and lower-left corners of the quadrilateral (major loop).

Inside the hysteresis major loop, the minor loop trajectories are given by

$$u(t) = \begin{cases} m_{h,t}v(t) + c_d & \text{if } \dot{v}(t) < 0 \\ m_{h,b}v(t) + c_u & \text{if } \dot{v}(t) > 0 \end{cases} \quad (3.9)$$

where c_d and c_u are the intersections with the u -coordinate axis in Fig. 3.1. Their values are restricted to the intervals $c_d \in (c_{h,t}, c_1)$ and $c_u \in (c_2, c_{h,b})$ and whose ends c_1 and c_2 are

$$c_1 = \begin{cases} (m_{h,b} - m_{h,t}) \frac{c_{h,b} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,b}} + c_{h,b} & \text{if } m_{h,t} < m_{h,b} \\ (m_{h,b} - m_{h,t}) \frac{c_{h,b} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,b}} + c_{h,b} & \text{if } m_{h,t} > m_{h,b} \\ c_{h,b} & \text{if } m_{h,t} = m_{h,b} \end{cases} \quad (3.10)$$

$$c_2 = \begin{cases} (m_{h,t} - m_{h,b}) \frac{c_{h,t} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,t}} + c_{h,t} & \text{if } m_{h,t} > m_{h,b} \\ (m_{h,t} - m_{h,b}) \frac{c_{h,t} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,t}} + c_{h,t} & \text{if } m_{h,t} < m_{h,b} \\ c_{h,t} & \text{if } m_{h,t} = m_{h,b} \end{cases} \quad (3.11)$$

The values of c_d and c_u depend on the extremum where $\dot{v}(t)$ changes sign and on the past trajectories of $(v(t), u(t))$. Eq. (3.9) – (3.11) denote the nonlocal memory characteristic of the hysteron.

Collecting all the piecewise representations, the hysteron output $u(t) = H(v(t))$ representing the motion of $u(t)$ and $v(t)$ on the half-lines (3.5), (3.6) and the segments (3.7), (3.8), and the minor loops (3.9) – (3.11) is fully described by

$$\dot{u}(t) = \begin{cases} m_{h,l} \dot{v}(t) & \text{if } v(t) \geq v_3 \text{ and } u(t) = m_{h,l} v(t) + c_{h,l}, \text{ or} \\ & \text{if } v_4 < v(t) < v_3, \dot{v}(t) < 0, \\ & u(t) = m_{h,l} v(t) + c_d, \\ & u(t) \neq m_{h,l} (v(t) - c_{h,l}) \text{ and} \\ & u(t) \neq m_{h,b} v(t) + c_{h,b}, \text{ or} \\ & \text{if } m_{h,l} < m_{h,b}, v_4 < v(t) < v_3, \\ & u(t) = m_{h,b} v(t) + c_{h,b} \text{ and } \dot{v}(t) < 0, \text{ or} \\ & \text{if } m_{h,l} < m_{h,b}, v_4 < v(t) < v_3, \\ & \dot{v}(t) > 0 \text{ and } u(t) = m_{h,l} v(t) + c_{h,l} \\ m_{h,b} \dot{v}(t) & \text{if } v(t) \leq v_4 \text{ and } u(t) = m_{h,b} v(t) + c_{h,b}, \text{ or} \\ & \text{if } v_4 < v(t) < v_3, \dot{v}(t) > 0, \\ & u(t) = m_{h,b} v(t) + c_u, \\ & u(t) \neq m_{h,r} (v(t) - c_{h,r}) \text{ and} \\ & u(t) \neq m_{h,l} v(t) + c_{h,l}, \text{ or} \\ & \text{if } m_{h,l} > m_{h,b}, v_4 < v(t) < v_3, \\ & u(t) = m_{h,l} v(t) + c_{h,l} \text{ and } \dot{v}(t) > 0, \text{ or} \\ & \text{if } m_{h,l} > m_{h,b}, v_4 < v(t) < v_3, \\ & \dot{v}(t) < 0 \text{ and } u(t) = m_{h,b} v(t) + c_{h,b} \\ m_{h,r} \dot{v}(t) & \text{if } v_4 < v(t) < v_3, \dot{v}(t) > 0 \text{ and} \\ & u(t) = m_{h,r} (v(t) - c_{h,r}) \\ m_{h,l} \dot{v}(t) & \text{if } v_4 < v(t) < v_3, \dot{v}(t) < 0 \text{ and} \\ & u(t) = m_{h,l} (v(t) - c_{h,l}) \\ 0 & \text{if } \dot{v}(t) = 0 \end{cases}$$

subject to : $m_{h,l} > 0, m_{h,r} > 0, \min(m_{h,l}, m_{h,r}) > m_{h,l} > 0, \min(m_{h,l}, m_{h,r}) > m_{h,b} > 0, c_{h,l} < c_{h,r},$
 $c_{h,l} > c_{h,b}$

(3.12)

Since the electromechanical-valve actuator used here is digitally controlled, the discrete-time version of Krasnosel'skii's hysteron, $H(v(k)) = u(k)$, is applied to model the hysteresis associated with our valve actuator. The symbol k denotes the index of the

digital sampled data. By replacing the time derivatives in Eq. (3.12) with v_d and v_u given as

$$v_d = \frac{m_{h,l}c_{h,l} + c_d}{m_{h,l} - m_{h,t}} \text{ and } v_u = \frac{m_{h,r}c_{h,r} + c_u}{m_{h,r} - m_{h,b}} \quad (3.13)$$

where $c_d = u(k-1) - m_{h,t}v(k-1)$ and $c_u = u(k-1) - m_{h,b}v(k-1)$

such that $v_4 \leq v_d \leq v_u \leq v_3$, the discrete-time hysteresis representation can be described by

$$H(v(k)) = u(k) = \begin{cases} u(k-1) & \text{if } v(k) = v(k-1) \\ m_{h,t}v(k) + c_{h,t} & \text{if } v(k) \geq v_1, \text{ or} \\ & \text{if } m_{h,t} < m_{h,b}, \\ & u(k-1) = m_{h,t}v(k-1) + c_{h,t} \text{ and} \\ & v(k-1) < v(k) < v_1 \\ m_{h,b}v(k) + c_{h,b} & \text{if } v(k) \leq v_2, \text{ or} \\ & \text{if } m_{h,t} > m_{h,b}, \\ & u(k-1) = m_{h,b}v(k-1) + c_{h,b} \text{ and} \\ & v_2 < v(k) < v(k-1) \\ m_{h,t}v(k) + c_d & \text{if } v_d < v(k) < v(k-1) \\ m_{h,b}v(k) + c_u & \text{if } v(k-1) < v(k) < v_u \\ m_{h,t}(v(k) - c_{h,t}) & \text{if } v_d \geq v(k) \geq v_2 \\ m_{h,r}(v(k) - c_{h,r}) & \text{if } v_u \leq v(k) \leq v_1 \end{cases} \quad (3.14)$$

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 variables v_1, v_2, v_u, v_d are given respectively by

$$v_1 = \frac{c_{h,t} + m_{h,r}c_{h,r}}{m_{h,r} - m_{h,t}}, \quad v_2 = \frac{c_{h,b} + m_{h,l}c_{h,l}}{m_{h,l} - m_{h,b}} \quad (3.15)$$

$$v_u = \frac{m_{h,r}c_{h,r} + c_u}{m_{h,r} - m_{h,b}}, \quad v_d = \frac{m_{h,l}c_{h,l} + c_d}{m_{h,l} - m_{h,t}} \quad (3.16)$$

where in Eq. (3.16), $c_u = u(k-1) - m_{h,b}v(k-1)$ and $c_d = u(k-1) - m_{h,t}v(k-1)$ such that

$$v_4 \leq v_d \leq v_u \leq v_3.$$

3.1.2 Actuator Model

Actuator model is the mathematical representation of the electromechanical-valve actuator used in the thesis. The actuator model, represented by $\hat{G}$, consists of two parts: 1) actuator position feedback control (G_{FB}) and 2) backlash (B).

The actuator position feedback characteristic is obtained from the calibration of the current command $v \in [4.00, 20.00 \text{ mA}]$ to the actuator position represented by the valve-opening angle $\theta \in [0.0, 90.0 \text{ degrees}]$ at steady state. The steady-state condition requires that no air pressure (no air flow) is exerted on either side of the valve and only the steady-state (static) values are taken for the calibration data. In doing so, G_{FB} can be treated as a time-invariant and the effect of nonlinearity such as hysteresis can be neglected. The calibration is done using an ammeter and a protractor to measure v and θ . The results are obtained in three trials and they are listed in Table 3.1. As seen from Table 3.1, the top and bottom figures on the v column denote the upper and lower limits of the actuator current command. Fig. 3.2 shows the calibration plot of v and the average valve-opening angle measured θ_{avg} .

$v \text{ [mA]}$	$\theta \text{ [deg]}$			
	Trial 1	Trial 2	Trial 3	$\theta_{avg} \text{ [deg]}$
5.90	0.0	0.0	0.0	0.0
10.00	30.0	30.0	29.5	29.8
12.00	45.0	45.5	45.0	45.2
14.00	59.5	60.0	60.0	59.8
18.16	90.0	89.5	89.5	89.7

Table 3.1: Calibration results of θ corresponding to v

Fig. 3.2: θ_{avg} vs v calibration plot

The calibration plot reveals a linear relationship between v and θ , which can be described by the linear function $G_{FB}(v(t))$ as

$$G_{FB}(v(t)) = \theta(t) = 7.34v(t) - 43.48 \quad (3.17)$$

Since the hysteresis model $H(v(t))$ is induced before the actuator, the current input to the actuator is actually the output u from $H(v(t))$. Thus, with the presence of actuator hysteresis, Eq. (3.17) is modified to

$$G_{FB}(u(t)) = G_{FB}(H(v(t))) = \theta(t) = 7.34u(t) - 43.48 \quad (3.18)$$

which represents the position feedback characteristic of our actuator model at any time t .

The backlash operator, B , represents the actuation backlash exists in actuator and/or position sensor (potentiometer). Since the position feedback controller from the manufacturer does not provide backlash compensation, thus, the input-output characteristic shows a typical backlash effect (Fig. 3.3).

Fig. 3.3: Backlash effect on the θ vs v relationship

The backlash effect is generally caused by the gear-train offset (Fig. 3.4) and the ball-valve surface friction between the valve ball and seat rings (Fig. 3.5).

Fig. 3.4: Gear-train offset

Fig. 3.5: Friction between valve ball and seat rings

The gear-train system installed on the actuator is a set of reduction gears connected between the actuator AC-motor and the valve stem, and between the valve stem and the potentiometer. The gear-train offset is usually fixed and it contributes to the deadband width of the backlash operator.

The valve ball is of the floating ball type where it is totally supported by a pair of resilient seat rings (see Fig. 3.5). The floating ball design allows line pressure to assist sealing by moving the closed ball into the downstream seat. However, this design increases the overall valve surface friction when it is subjected to higher pressures. Thus, the gain of the backlash changes when the valve is subjected to the change in pressure. The valve surface friction, which in general, is dominated by Coulomb or dry friction [33, 45].

Coulomb friction, $F_{fri,c}$, is considered to be a rate independent (independent of velocity) friction force given by

$$F_{fri,c} = \text{sign}(\dot{\theta})\mu F_N \quad (3.19)$$

where F_N is the net force acting on the contacting valve seat rings caused by the line pressure difference, $\text{sign}(\cdot)$ is the function which changes the sign of $F_{fri,c}$ according to the direction of valve motion $\dot{\theta}$ such that the sign is always opposite to the direction of $\dot{\theta}$, and $\mu \in [0,1]$ is the friction coefficient which is affected by viscosity due to changes in temperature, lubrication, surface roughness, etc. The friction coefficient μ consists of two parts: static friction coefficient, μ_s , and kinetic friction coefficient, μ_k , where $\mu_s > \mu_k$. μ reaches a maximum, μ_s , if the valve just starts to move from its static position. Once the valve starts moving, the friction force is dominated by the kinetic friction μ_k and the magnitude of μ begins to drop.

According to the manufacturer's specification, the maximum torque provided by the actuator motor is 200 lb-in, which is sufficient enough to overcome the maximum valve surface friction exerted at our working condition. If the compressed air supply to our pneumatic system is consistent in terms of pressure and temperature, three assumptions can be made about the actuation backlash: 1) the deadband of the backlash operator is considered to be static since it is caused by the fixed gear-train offset; 2) at our working condition, the ball-valve surface friction is consistent as defined by Eq.

(3.19) and is sufficiently small to be overcome by the available torque of the actuator, thus, the gain of the backlash operator is considered to be static; 3) from assumption 1) and 2), the backlash operator is considered to be static.

The backlash operator, B , is described by two parallel straight lines connected with horizontal line segments depicted in Fig. 3.6.

Fig. 3.6: Graphical description of a typical backlash operator

Tao and Kokotović *et al.* have described the output of the backlash operator $u(t) = B(v(t)) = B(m_b, c_{b,l}, c_{b,r}; v(t))$ as upward side motion and downward side motion connected by a deadband. The upward side is active when both $v(t)$ and $u(t)$ increase, given by

$$u(t) = m_b(v(t) - c_{b,r}); \dot{v}(t) > 0, \dot{u}(t) > 0 \quad (3.20)$$

The downward side is active when both $v(t)$ and $u(t)$ decrease, given by

$$u(t) = m_b(v(t) - c_{b,l}); \dot{v}(t) < 0, \dot{u}(t) < 0 \quad (3.21)$$

where the slope $m_b > 0$, and the left and right zero crossings $c_{b,l} < c_{b,r}$ are constants and the motion on any inner segment is characterized by $\dot{u}(t) = 0$. Then, combining Eq. (3.20) and (3.21), a compact description of backlash $B(\cdot)$ is described by

$$\dot{u}(t) = \begin{cases} m_b \dot{v}(t) & \text{if } \dot{v}(t) > 0 \text{ and } u(t) = m_b(v(t) - c_{b,r}), \text{ or} \\ & \text{if } \dot{v}(t) < 0 \text{ and } u(t) = m_b(v(t) - c_{b,l}) \\ 0 & \text{otherwise} \end{cases} \quad (3.22)$$

subject to : $m_b > 0, c_{b,l} < c_{b,r}$

To utilize the backlash operator $B(\cdot)$ into a digital control system, Eq. (3.22) is converted to a discrete-time version. To do so, the term $v(t)$ is replaced by another set of parameters v_l and v_r to describe the direction of motion, given by

$$v_l = u(k-1) / m_b + c_{b,l} \quad (3.23)$$

$$v_r = u(k-1) / m_b + c_{b,r} \quad (3.24)$$

where k is the index of the digital sampled data. Eq. (3.23) and (3.24) represent the v -axis projections of the intersections of the two parallel lines of slope m_b with the horizontal inner segment containing $u(t-1)$. Thus, the discrete-time equation is given by

$$\begin{aligned}
 B(v(k)) &= u(k) \\
 &= \begin{cases} m_b(v(k) - c_{b,l}) & \text{if } v(k) \leq v_l \\ m_b(v(k) - c_{b,r}) & \text{if } v(k) \geq v_r \\ u(k-1) & \text{if } v_l < v(k) < v_r \end{cases} \quad (3.25) \\
 &\text{subject to : } m_b > 0, c_{b,l} < c_{b,r}
 \end{aligned}$$

Cascading G_{FB} given in Eq. (3.18) and B given in Eq. (3.25), the actuator model $\hat{G}$ is thus described by

$$\begin{aligned}
 \hat{G}(B(u(k))) = \hat{\theta}(k) &= -43.48 + 7.34 \begin{cases} m_b(u(k) - c_{b,l}) & \text{if } u(k) \leq v_l \\ m_b(u(k) - c_{b,r}) & \text{if } u(k) \geq v_r \\ B(u(k)) & \text{if } v_l < u(k) < v_r \end{cases} \quad (3.26) \\
 &\text{subject to : } m_b > 0, c_{b,l} < c_{b,r}
 \end{aligned}$$

with v_l and v_r become

$$v_l = \frac{B(u(k-1))}{m_b} + c_{b,l} \quad (3.27)$$

$$v_r = \frac{B(u(k-1))}{m_b} + c_{b,r} \quad (3.28)$$

The backlash parameters m_b , $c_{b,l}$, and $c_{b,r}$ are parameters to be identified together with the induced actuator hysteresis using the GAASS method. Since the feedback control loop and the backlash effect are assumed to be consistence with time, the parameters m_b , $c_{b,l}$, and $c_{b,r}$ are static values.

For the convenience of flow calculation, the output of $\hat{G}$ is expressed as a percent of maximum flow area %A. The function of %A is converted from the ball valve characteristic chart. A typical ball valve characteristic is shown in Fig. 3.7, which depicts a plot of percent of maximum flow area %A versus valve ball rotation θ provided by Fisher Controls Company [50].

Fig. 3.7: Ball valve characteristic

Approximating the plot in Fig. 3.7 by the third-order polynomial, %A is given by

$$\%A = 0.0002\theta^3 - 0.0080\theta^2 + 0.4521\theta - 1.6320 \quad (3.29)$$

Note that in Fig. 3.7, the percent of maximum flow area %A is zero until the minimum valve ball rotation θ of approximately 5 degrees is reached. The occurrence of this dead zone effect is due to the overlapping area of the waterway and the valve ball opening, which is intended to ensure a tight closure when the valve is closed.

3.1.3 Plant Model

The plant model, $\hat{P}$, is a mathematical model of the pneumatic system, which belongs to the aircraft engine bleed-air control test rig (see Fig. 5.1 – 5.3). The pneumatic system allows air to flow from the pressure vessels into the atmosphere through the control of the electromechanical-valve actuator G . The output of the plant are mass flow rate W and duct pressure p which are modeled by the adiabatic flow equation given in Eq. (3.30) and the total pressure equation given in Eq. (3.31), respectively as

$$W = \frac{c_d \%A A_{\max} p_1}{\sqrt{T_1}} \sqrt{\left[\frac{2\gamma g}{(\gamma-1)R} \right] \left[\left(\frac{p_2}{p_1} \right)^{2/\gamma} - \left(\frac{p_2}{p_1} \right)^{(1+\gamma)/\gamma} \right]}$$

$$\frac{p_2}{p_1} = 0.8 \quad \text{if} \quad \frac{p_2}{p_1} \leq 0.8 \quad (\text{choke factor for ball valve}) \quad (3.30)$$

$$\text{and} \quad T_1 = T_{\text{vessel}} \frac{p_2}{p_1}^{(\gamma-1)/\gamma}$$

$$p_1 = p_t - \frac{1}{2} \bar{\rho} \bar{V}^2$$

$$\bar{\rho} = \frac{\left(\frac{p_1 + p_2}{2} \right)}{R \left(\frac{T_1 + T_2}{2} \right)} \quad \text{and} \quad \bar{V} = \frac{W}{\bar{\rho} \left(\frac{A_{CV} + A_{\max}}{2} \right)} \quad (3.31)$$

where W denotes the mass flow rate in lbm/s, c_d denotes the discharge coefficient $\cong 0.65$, $\%A$ denotes the percent of maximum valve flow area, $A_{\max}$ denotes the valve maximum flow area $\cong 0.4418 \text{ in}^2$, A_{CV} denotes the exact valve flow area $= (\%A)A_{\max}$, g denotes the gravity constant $\cong 386.4 \text{ in/s}^2$, γ denotes the isentropic coefficient $\cong 1.4$, R denotes the universal gas constant $\cong 639.6 \text{ Btu/}^\circ\text{R}$, p denotes the duct static pressure in psia, T denotes the static temperature in $^\circ\text{R}$, $\bar{\rho}$ denotes the mean air density in lbm/in³, $\bar{V}$ denotes the mean air velocity in in/s, and the subscripts, 1, 2, t , $vessel$ denote air properties upstream, downstream, at stagnation (when control valve is fully-closed), and at pressure vessels, respectively. Since the downstream location is located at the exit of the pneumatic system, thus, the downstream air properties are assumed to be at standard sea-level atmospheric condition ($p_2 \cong p_{\text{amb}}$, $T_2 \cong T_{\text{amb}}$) at all time. Also, the temperature of the pressure vessels are assumed to be maintained at ambient temperature and the volume of the vessels is large enough such that air temperature inside the vessels does not change significantly, thus, $T_{\text{vessel}} \cong T_{\text{amb}}$ at any time.

The valve upstream pressure, p_1 in Eq. (3.30) and (3.31) is a steady-state value. In fact, due to the flow impedance of the pneumatic system, p_1 has a dynamic response. Experimental results have shown that the dynamic response is closely matched with the first-order system response. Fig. 3.8 shows a pressure step change of 10 to 15 psig at $t = 0$ reveals the first-order system response.

Fig. 3.8: First-order system response of a pressure step change in the pneumatic system

Hence, the valve upstream static pressure with the first-order system response at any time t becomes

$$\hat{p}_1(t) = \mathcal{L}^{-1} \left[\frac{p_1(s)}{s+1} \right]; \quad [0 < \tau < 1] \quad (3.32)$$

where $\hat{p}_1$ is the first-order transient response of p_1 and τ is the flow time constant which changes according to the flow impedance. τ is a parameter to be identified together with the induced actuator hysteresis using the GAASS method. Assuming that the flow properties during the hysteresis identification period are consistent, τ can be considered as a static value.

3.2 Sensor Measurements for The Actuator Hysteresis Parameters Identification

In system identification, both the input and output signals are typically required for computation. The system input is usually known. However, the system output can be any physical change resulted from the change of the input to the system. For the case of

actuators, the most desirable system output is the position sensor measurement. However, in some applications such as valve actuators used in large pneumatic pipelines and aircraft ECS units, position sensors are usually not present. In such cases, the system output has to be acquired from other devices in the system, such as the pressure sensor, temperature sensor, and/or flow sensor, etc. Since the accuracy of the identified system parameters may depend on the type of available sensor measurement, we have investigated three scenarios with the assumptions that the system output is acquired from a position sensor, a pressure sensor, and a flow sensor, respectively. For each scenario, the hysteresis identification and compensation using hysteresis inverse model are performed, and the results are compared with each other.

3.2.1 Position Sensor Measurement

Position sensor measures the actuator (valve-opening) position directly. It is a linear-character potentiometer attached to the gear-train unit of the drive shaft which provides a voltage feedback corresponds to the actuator position. The accuracy of the position sensor measurement is affected by the gear-train offset and the linearity tolerance of the potentiometer. The specifications of the actuator position sensor provided by the manufacturer, BI-TORQ, CARBO-BOND, Inc., are shown in Table 3.2.

Specifications of The Actuator Position Sensor (potentiometer)	
Range of Resistance [Ω]	1 - 100 K
Linearity	$\pm 11 \%$

Table 3.2: Specifications of the actuator position sensor

As a direct feedback, the sensor dynamics is usually neglected. Thus, less work is required for the signal processing because sensor dynamics is not considered. Since the position sensor has not been calibrated by the manufacturer, a calibration is done by the author to get the relationship between the valve-opening angle θ and the position sensor voltage output V_P . The calibration results are obtained from the v - θ calibration listed in Table 3.1 of Section 3.1.2. The valve-opening angles measured by the position sensor in voltage V_P are given in Table 3.3. Fig. 3.9 shows the calibration plot of the average valve-opening angle θ_{avg} and the average position sensor measurement $V_{P,avg}$ reveals a linear relationship.

v [mA]	Trial 1		Trial 2		Trial 3		θ_{avg} [deg]	$V_{p,avg}$ [V]
	θ [deg]	V_P [V]	θ [deg]	V_P [V]	θ [deg]	V_P [V]		
5.90	0.0	2.83	0.0	2.87	0.0	2.87	0.0	2.86
10.00	30.0	3.51	30.0	3.54	29.5	3.55	29.8	3.53
12.00	45.0	3.85	45.5	3.87	45.0	3.89	45.2	3.87
14.00	59.5	4.17	60.0	4.18	60.0	4.19	59.8	4.18
18.16	90.0	4.80	89.5	4.80	89.5	4.79	89.7	4.80

Table 3.3: Calibration results of θ corresponding to v

Fig. 3.9: θ_{avg} vs $V_{P,avg}$ calibration plot

Hence, the valve-opening angle measurement θ_m can be given by a linear transformation of the position sensor voltage output V_P as

$$\theta_m(V_P(t)) = \frac{V_P(t) - 2.849}{0.022} \quad (3.33)$$

where $V_P(t) \in [2.849, 4.811 \text{ V}]$ and $\theta_m(V_P(t)) \in [0, 90 \text{ deg}]$.

As a result, when using the position sensor measurement to perform the actuator hysteresis identification, the dimension of the parameter space X (Eq. (3.1)) becomes eleven: three for the actuation backlash B (Eq. (3.25)) and eight for the actuator hysteresis H (Eq. (3.14)).

3.2.2 Pressure Transducer Measurement

Pressure transducer measures the system output in terms of the valve upstream pressure. The accuracy of the pressure transducer measurement is affected not only by the actuator gear-train offset, but a number of other factors, such as the measurement precision of the pressure transducer, leakage along the pneumatic duct line, and the aerodynamic interaction along the duct, etc. Thus, the discrepancy of this measurement is relatively higher than that of the position sensor when it is used to represent the system output. The specifications of the pressure transducer provided by the manufacturer, Omega Instrument, Inc., are shown in Table 3.4.

Specifications of The Pressure Transducer	
Range of Input [psig]	0 – 100
Range of Output [Vdc]	1.0 - 11.0
Accuracy (linearity, hysteresis, repeatability)	± 0.25 % full-scale
Response Time [ms]	1
Pressure Port Diameter [in]	1/4 NPT
Proof Pressure [psig]	200

Table 3.4: Specifications of the pressure transducer

The sensor dynamics of the pressure transducer is negligible since its response time is only 1 millisecond, which is much shorter than the controller's sampling time of 0.5 second. From the specifications provided by the manufacturer, the static pressure measurement p_m can be given by a linear transformation of the pressure transducer voltage output V_{PS} as

$$p_m(V_{PS}(t)) = 10(V_{PS}(t) - 1.0) \quad (3.34)$$

where $V_{PS}(t) \in [1.0, 11.0 \text{ V}]$ and $p_m(V_{PS}(t)) \in [0, 100 \text{ psig}]$. In our system, the pressure transducer measures the valve upstream static pressure represented by $p_{1,m}$.

Since the valve upstream pressure demonstrates a first-order system response according to Eq. (3.32), the dimension of the parameter space X (Eq. (3.1)) extends to twelve when using the pressure transducer measurement as the system output: three for the actuation backlash B (Eq. (3.25)), eight for the actuator hysteresis H (Eq. (3.14)), and one for the valve upstream pressure dynamics $\hat{p}_1$ (Eq. (3.32)).

3.2.3 Thermistor Flow Sensor Measurement

Thermistor flow sensor provides an alternative to measure the system output in terms of the mass flow rate. The accuracy of the thermistor flow sensor measurement is mainly affected by sensor dynamics, precision of the sensor, and aerodynamic interaction along the duct. Thus, the discrepancy of this measurement is relatively higher than that of the position sensor when it is used to represent the system output. The thermistor flow sensor has been calibrated in our pneumatic system from the thermistor Reynolds numbers Re_d between 920 to 5120, which corresponds to a flow range of 0.02 to 0.12 lbm/s. The flow rate measurement W_m is calibrated as a conversion of the flow sensor voltage output V_{FS} given by

$$W_m(V_{FS}(t)) = 4.1428 \times 10^{-4} (V_{FS}(t))^{4.6083} \quad (3.35)$$

where $W_m \in [0.02, 0.12 \text{ lbm/s}]$. Since the dynamic response for thermistor flow sensors is usually in the seconds range, sensor dynamics has to be taken into account. Indeed, experimental results within this flow range have shown that the dynamic response of the thermistor flow sensor is closely matched with the second-order underdamped system response. Fig. 3.10 shows a flow step change reveals the second-order underdamped system response.

Fig. 3.10: Second-order sensor response of a flow step change in the pneumatic system

In Fig. 3.10, the flow step input is calculated by Eq. (3.30) while the flow response is measured by the thermistor flow sensor. The output of the thermistor flow sensor, $\hat{W}$, can be approximated by the second-order underdamped system response given as

$$\hat{W}(t) = \mathcal{L}^{-1} \left[\frac{W(s)\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \right]; [0 < \zeta < 1 \text{ for underdamped response}] \quad (3.36)$$

where W denotes the true mass flow rate given in Eq. (3.30), ζ denotes the damping ratio, and ω_n denotes the natural frequency in rad/s of the dynamic response. Both ζ and ω_n are influential by W and are parameters to be identified together with the induced actuator hysteresis using the GAASS method. Assuming that the air properties during the hysteresis identification period are consistent, ζ and ω_n can be treated as static values.

Since the flow sensor response demonstrates a second-order system response according to Eq. (3.36), the dimension of the parameter space X (Eq. (3.1)) extends to thirteen when using the thermistor flow sensor measurement as the system output: three for the actuation backlash B (Eq. (3.25)), eight for the actuator hysteresis H (Eq. (3.14)), and two for the flow sensor dynamics $\hat{W}$ (Eq. (3.36)).

3.3 Hysteresis Inverse Compensation

In system inverse compensation, the inverse model is used as a model-based, feed-forward compensator to soften or cancel the effect of the induced nonlinearity [31, 43]. For the induced actuator hysteresis here, the hysteresis inverse model with nonlocal memory $H^{-1}(\hat{m}_{h,l}, \hat{m}_{h,r}, \hat{m}_{h,l}, \hat{m}_{h,b}, \hat{c}_{h,l}, \hat{c}_{h,r}, \hat{c}_{h,l}, \hat{c}_{h,b}; u_d(t))$ developed by Tao and Kokotović *et al.* [43], is applied to soften the hysteresis effect. The hysteresis parameters $\hat{m}_{h,l}, \hat{m}_{h,r}, \hat{m}_{h,l}, \hat{m}_{h,b}, \hat{c}_{h,l}, \hat{c}_{h,r}, \hat{c}_{h,l}, \hat{c}_{h,b}$ are values identified using the GAASS method described in Section 3.1 and u_d is the control input. Fig. 3.11 illustrates the graphical description of this hysteresis inverse model.

Fig. 3.11: Graphical description of Tao and Kokotović's hysteresis inverse model

According to Tao and Kokotović *et al.*, the output of this hysteresis inverse model, $v(t)$ is described by two half-lines

$$v(t) = \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_{h,t}), u_d(t) > u_1 = \frac{\hat{m}_{h,l} (\hat{m}_{h,t} \hat{c}_{h,l} + \hat{c}_{h,t})}{\hat{m}_{h,l} - \hat{m}_{h,t}} \quad (3.37)$$

$$v(t) = \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_{h,b}), u_d(t) < u_2 = \frac{\hat{m}_{h,r} (\hat{m}_{h,b} \hat{c}_{h,r} + \hat{c}_{h,b})}{\hat{m}_{h,r} - \hat{m}_{h,b}} \quad (3.38)$$

and two line segments

$$v(t) = \frac{1}{\hat{m}_{h,r}} u_d(t) + \hat{c}_{h,r}, u_2 \leq u_d(t) < u_3 = \frac{\hat{m}_{h,r} (\hat{m}_{h,t} \hat{c}_{h,r} + \hat{c}_{h,t})}{\hat{m}_{h,r} - \hat{m}_{h,t}} \quad (3.39)$$

$$v(t) = \frac{1}{\hat{m}_{h,l}} u_d(t) + \hat{c}_{h,l}, \frac{\hat{m}_{h,l} (\hat{m}_{h,b} \hat{c}_{h,l} + \hat{c}_{h,b})}{\hat{m}_{h,l} - \hat{m}_{h,b}} = u_4 < u_d(t) \leq u_1 \quad (3.40)$$

where u_1 , u_2 , u_3 , and u_4 are the values of $u_d(t)$ at the lower-right, upper-left, upper-right, and lower-left corners of the quadrilateral formed by the half-lines in (3.37) – (3.38) and segments in (3.39) – (3.40).

Along the segments, the time derivatives of $v(t)$, $u_d(t)$ are of constant sign, given by

$$\dot{u}_d(t) > 0, \dot{v}(t) > 0 \quad \text{if } v(t) = \frac{1}{\hat{m}_{h,r}} u_d(t) + \hat{c}_{h,r} \quad (3.41)$$

$$\dot{u}_d(t) < 0, \dot{v}(t) < 0 \quad \text{if } v(t) = \frac{1}{\hat{m}_{h,l}} u_d(t) + \hat{c}_{h,l} \quad (3.42)$$

Combining the time derivatives in (3.41) – (3.42), $v(t)$ inside the loop formed by the half-lines (3.37) – (3.38) and the line segments (3.39) – (3.40) is thus given by

$$v(t) = \begin{cases} \frac{1}{\hat{m}_{h,l}} (u_d(t) - \hat{c}_w) & \text{if } \dot{u}_d(t) < 0 \\ \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_e) & \text{if } \dot{u}_d(t) > 0 \end{cases} \quad (3.43)$$

where $\hat{c}_w \in (\hat{c}_{h,l}, \hat{c}_1)$, $\hat{c}_e \in (\hat{c}_2, \hat{c}_{h,b})$ are quantities which depend on the point $(u_d(t), v(t))$

where $\dot{u}_d(t)$ changes the sign, with

$$\hat{c}_1 = \begin{cases} \left(\hat{m}_{h,b} - \hat{m}_{h,l} \right) \frac{\hat{c}_{h,b} + \hat{m}_{h,l} \hat{c}_{h,l}}{\hat{m}_{h,l} - \hat{m}_{h,b}} + \hat{c}_{h,b} & \text{if } \hat{m}_{h,l} < \hat{m}_{h,b} \\ \left(\hat{m}_{h,b} - \hat{m}_{h,l} \right) \frac{\hat{c}_{h,b} + \hat{m}_{h,r} \hat{c}_{h,r}}{\hat{m}_{h,r} - \hat{m}_{h,b}} + \hat{c}_{h,b} & \text{if } \hat{m}_{h,l} > \hat{m}_{h,b} \\ \hat{c}_{h,b} & \text{if } \hat{m}_{h,l} = \hat{m}_{h,b} \end{cases} \quad (3.44)$$

$$\hat{c}_2 = \begin{cases} \left(\hat{m}_{h,l} - \hat{m}_{h,b} \right) \frac{\hat{c}_{h,l} + \hat{m}_{h,r} \hat{c}_{h,r}}{\hat{m}_{h,r} - \hat{m}_{h,l}} + \hat{c}_{h,l} & \text{if } \hat{m}_{h,l} > \hat{m}_{h,b} \\ \left(\hat{m}_{h,l} - \hat{m}_{h,b} \right) \frac{\hat{c}_{h,l} + \hat{m}_{h,l} \hat{c}_{h,l}}{\hat{m}_{h,l} - \hat{m}_{h,b}} + \hat{c}_{h,l} & \text{if } \hat{m}_{h,l} < \hat{m}_{h,b} \\ \hat{c}_{h,l} & \text{if } \hat{m}_{h,l} = \hat{m}_{h,b} \end{cases} \quad (3.45)$$

Combining Eq. (3.37) – (3.43), the motion of $u_d(t)$ and $v(t)$ along the half-lines, the line segments, and around the inside loops is completely described by Eq. (3.46) as

$$\begin{aligned}
\dot{v}(t) = & \left\{ \begin{array}{ll}
\frac{1}{\hat{m}_{h,t}} \dot{u}_d(t) & \text{if } u_d(t) \geq u_3 \text{ and} \\
& v(t) = \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_{h,t}), \text{ or} \\
& \text{if } u_4 < u_d(t) < u_3, \dot{u}_d(t) < 0, \\
& v(t) = \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_w), \\
& v(t) \neq \frac{1}{\hat{m}_{h,t}} u_d(t) + \hat{c}_{h,t} \text{ and} \\
& v(t) \neq \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_{h,b}), \text{ or} \\
& \text{if } \hat{m}_{h,t} < \hat{m}_{h,b}, u_4 < u_d(t) < u_3, \\
& \dot{u}_d(t) < 0 \text{ and } v(t) = \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_{h,b}), \text{ or} \\
& \text{if } \hat{m}_{h,t} < \hat{m}_{h,b}, u_4 < u_d(t) < u_3, \\
& \dot{u}_d(t) > 0 \text{ and } v(t) = \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_{h,t}) \\
\\
\frac{1}{\hat{m}_{h,b}} \dot{u}_d(t) & \text{if } u_d(t) \leq u_4 \text{ and} \\
& v(t) = \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_{h,b}), \text{ or} \\
& \text{if } u_4 < u_d(t) < u_3, \dot{u}_d(t) > 0, \\
& v(t) = \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_e), \\
& v(t) \neq \frac{1}{\hat{m}_{h,r}} u_d(t) + \hat{c}_{h,r} \text{ and} \\
& v(t) \neq \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_{h,t}), \text{ or} \\
& \text{if } \hat{m}_{h,t} > \hat{m}_{h,b}, u_4 < u_d(t) < u_3, \\
& \dot{u}_d(t) > 0 \text{ and } v(t) = \frac{1}{\hat{m}_{h,t}} (u_d(t) - \hat{c}_{h,t}), \text{ or} \\
& \text{if } \hat{m}_{h,t} > \hat{m}_{h,b}, u_4 < u_d(t) < u_3, \\
& \dot{u}_d(t) < 0 \text{ and } v(t) = \frac{1}{\hat{m}_{h,b}} (u_d(t) - \hat{c}_{h,b}) \\
\\
\frac{1}{\hat{m}_{h,r}} \dot{u}_d(t) & \text{if } u_4 < u_d(t) < u_3, \dot{u}_d(t) > 0 \text{ and} \\
& v(t) = \frac{1}{\hat{m}_{h,r}} u_d(t) + \hat{c}_{h,r} \\
\\
\frac{1}{\hat{m}_{h,l}} \dot{u}_d(t) & \text{if } u_4 < u_d(t) < u_3, \dot{u}_d(t) < 0 \text{ and} \\
& v(t) = \frac{1}{\hat{m}_{h,l}} u_d(t) + \hat{c}_{h,l} \\
\\
0 & \text{if } \dot{u}_d(t) = 0
\end{array} \right.
\end{aligned} \tag{3.46}$$

Since the actuator is controlled digitally, a discrete-time version of the hysteresis inverse model is used. Hence, Eq. (3.46) is modified to

$$H^{-1}(u_d(k)) = v(k) = \begin{cases} v(k-1) & \text{if } u_d(k) = u_d(k-1) \\ \frac{1}{\hat{m}_{h,l}}(u_d(k) - \hat{c}_{h,l}) & \text{if } u_d(k) \geq u_1, \text{ or} \\ & \text{if } \frac{1}{\hat{m}_{h,l}} > \frac{1}{\hat{m}_{h,b}}, \\ & u_d(k-1) < u_d(k) < u_1, \text{ and} \\ & v(k-1) = \frac{1}{\hat{m}_{h,l}}(u_d(k-1) + \hat{c}_{h,l}) \\ \frac{1}{\hat{m}_{h,b}}(u_d(k) - \hat{c}_{h,b}) & \text{if } u_d(k) \leq u_2, \text{ or} \\ & \text{if } \frac{1}{\hat{m}_{h,l}} < \frac{1}{\hat{m}_{h,b}}, \\ & u_d(k-1) < u_d(k) < u_2, \text{ and} \\ & v(k-1) = \frac{1}{\hat{m}_{h,b}}(u_d(k-1) + \hat{c}_{h,b}) \\ \frac{1}{\hat{m}_{h,r}}u_d(k) + \hat{c}_{h,r} & \text{if } u_1 \geq u_d(k) \geq u_e \\ \frac{1}{\hat{m}_{h,l}}u_d(k) + \hat{c}_{h,l} & \text{if } u_2 \leq u_d(k) \leq u_w \\ \frac{1}{\hat{m}_{h,l}}(u_d(k) - c_w) & \text{if } u_w < u_d(k) < u_d(k-1) \\ \frac{1}{\hat{m}_{h,b}}(u_d(k) - c_e) & \text{if } u_d(k-1) < u_d(k) < u_e \end{cases} \quad (3.47)$$

subject to : $\hat{m}_{h,l} > 0, \hat{m}_{h,r} > 0, \min(\hat{m}_{h,l}, \hat{m}_{h,r}) > \hat{m}_{h,l} > 0, \min(\hat{m}_{h,l}, \hat{m}_{h,r}) > \hat{m}_{h,b} > 0, \hat{c}_{h,l} < \hat{c}_{h,r},$
 $\hat{c}_{h,l} > \hat{c}_{h,b}$

where u_1 and u_2 are the upper and lower limits of the control input (u_d) range, and the parameters c_e, c_w, u_e, u_w are given by

$$c_e = u_d(k-1) - \hat{m}_{h,b}v(k-1) \quad (3.48)$$

$$c_w = u_d(k-1) - \hat{m}_{h,l}v(k-1) \quad (3.49)$$

$$u_e = \frac{\hat{m}_{h,r}(\hat{m}_{h,b}\hat{c}_{h,r} + c_e)}{\hat{m}_{h,r} - \hat{m}_{h,b}} \quad (3.50)$$

$$u_w = \frac{\hat{m}_{h,l}(\hat{m}_{h,l}\hat{c}_{h,l} + c_w)}{\hat{m}_{h,l} - \hat{m}_{h,l}} \quad (3.51)$$

The hysteresis inverse model given in Eq. (3.47) is cascaded before the hysteresis model to perform the feed-forward compensation.

CHAPTER 4 SIMULATION OF THE HYSTERESIS PARAMETERS IDENTIFICATION AND HYSTERESIS INVERSE COMPENSATION

4.1 Configurations of The Simulation Model

The simulation model demonstrates the robustness of the proposed GAASS method in hysteresis parameters identification and the effectiveness of the hysteresis inverse compensation in actuator position control. In order to construct a more practical model that emulates closely to the experiment apparatus, real experimental data are used in constructing the hysteresis identification model. The experimental data are applied to estimate the actuation backlash, duct pressure dynamics, and thermistor flow sensor dynamics such that a more realistic identification model can be constructed.

The simulation procedure consists of six parts: 1) input data selection, 2) parametric identification of the actuation backlash, 3) non-parametric identification of the duct pressure dynamics, 4) non-parametric identification of the thermistor flow sensor dynamics, 5) simulation of the parametric identification of the predefined actuator hysteresis, and 6) simulation of the actuator hysteresis inverse compensation. Procedures 2) – 4) are conducted to estimate the initial working ranges of actuation backlash, duct pressure dynamics, and flow sensor dynamics without the presence of the induced actuator hysteresis. The identification results of 2) – 4) will then be used to set the appropriate search domains for the simulation of 5) with the induction of the predefined actuator hysteresis.

The simulation is started by selecting the appropriate input signal in 1) that is used for each system identification. Then, each selected input signal is passed onto the GAASS method to perform the identification of 2), 3), and 4) independently. Next, using the identification results from 2) – 4), the appropriate search domains for each system are chosen and the identification of the induced actuator hysteresis is performed subsequently. Lastly, the identified hysteresis parameters are fed to a hysteresis inverse model to carry out the simulation of the actuator hysteresis inverse compensation. All parts mentioned above are conducted under the air condition listed in Table 4.1.

Air Properties			
p_t [psig]	p_{amb} [psia]	T_{amb} [deg. R]	$\bar{\rho}$ [slug/in ³]
30	14.7	530	1.26E-06

Table 4.1: Air condition

4.1.1 Input Signal Selection

The input signal v is used to perturb the system (see Fig. 3.1) such that information about the unknown system (i.e. actuation backlash, duct pressure dynamics, thermistor flow sensor dynamics, and actuator hysteresis) can be learnt from its output resulting from the input trajectory. An appropriate input signal used for the system perturbation should have sufficient change in amplitude so that the change of the output signals is measurable by sensors. For the non-parametric identifications of the duct pressure dynamics and the thermistor flow sensor dynamics, the step function is chosen as the inputs because of its simplicity and the rapid change in amplitude. The magnitudes of these step functions are chosen such that they cover most of the controllable regions in the experiment. Eq. (4.1) and (4.2) show the step current commands used in the identification of the duct pressure dynamics and the identification of the thermistor flow sensor dynamics, respectively as

$$v(t) = \begin{cases} 11.0 & \text{if } t \leq 0 \\ 8.5 & \text{if } t > 0 \end{cases} \quad [\text{mA}] \quad (4.1)$$

$$v(t) = \begin{cases} 8.5 & \text{if } t \leq 0 \\ 12.5 & \text{if } t > 0 \end{cases} \quad [\text{mA}] \quad (4.2)$$

For the parametric identifications of the actuation backlash and the actuator hysteresis model, the input signals are chosen such that they can provide enough travels in the entire backlash operator and hysteresis model. The sufficient travelling of input signals in the backlash operator and the hysteresis model is essential because more information about the properties of backlash and hysteresis can be learnt. Hence, more accurate parameter values can be identified. The ideal input with such trajectory should contain both upward and downward motions and with a variation in the trajectory amplitudes. In this thesis, a sinusoidal current command with decaying amplitude is used. This sinusoidal function, given in Eq. (4.3), is chosen such that it always gives measurable outputs at any time during the perturbation period.

$$v(t) = 9.0 + 2.0 \exp(-0.01t) \sin\left(\frac{2\pi t}{10}\right) \text{ [mA]} \quad (4.3)$$

The lengths of the perturbation period (data acquisition period) are different for different system identifications. In general, systems of high complexities and/or with slow dynamics require longer data acquisition period to get the vital information about the system properties. Vice versa, systems of low complexities and/or with fast dynamics do not require long data acquisition period to get the necessary information about their properties. The data sampling time used here is 0.5 second which is sufficient enough for data acquisitions of all systems employed in the thesis since the systems to be identified are all static and do not have fast system dynamics. Table 4.2 shows the data sampling time and the data acquisition period used for each system identification in this thesis.

Type of System Identification	Data Sampling Time [sec]	Data Acquisition Period [sec]	Sensor(s) Used
Actuation backlash	0.5	60	Position sensor
p_1 1st-order system dynamics		10	Pressure transducer
Flow sensor 2nd-order system dynamics		60	Thermistor flow sensor
Actuator hysteresis		60	Position sensor/Pressure transducer/Thermistor flow sensor

Table 4.2: Data acquisition in different system identifications

4.1.2 Parametric Identification of The Actuation Backlash

The parametric identification of the actuation backlash, $B(\cdot)$, is performed using the GAASS method illustrated in Fig. 4.1. This part is done experimentally using the valve-opening position measurement θ_m as the actual output.

Fig. 4.1: Parametric identification of actuation backlash using the GAASS method

In this actuation backlash identification, the parameters to be identified are the backlash parameters m_b , $c_{b,l}$, and $c_{b,r}$ in the actuator model $\hat{G}(B(\cdot))$. The input signal v is given in Eq. (4.3) and the simulated output $\hat{\theta}$ is the valve-opening position calculated by the actuator model $\hat{G}$, given in Eq. (3.26). The plant model $\hat{P}$ is described by Eq. (3.30) for the air flow model and Eq. (3.31) – (3.32) for the first-order duct pressure dynamics model. The GAASS method continuously searches for the best value of the backlash parameters until the maximum number of generations, $gen = 200$ is reached (stop criterion). The parameter settings of the actuation backlash identification are summarized in Table 4.3.

Sensor Used	GAASS Parameters					Input (v)	Mapping Model	Parameter Set	Search Domain
	$Npop$	gen	c/ξ	$pc,l/pc,h$	$pm,l/pm,h$				
Position sensor	5	200	0.02/ 0.05	0.5/0.9	0.01/0.1	Sinusoidal Eq. (4.3)	$\hat{G}$ Eq. (3.26)	$\{m_b \mid m_b > 0\}$	[0, 10.00]
								$\{c_{b,l} \mid c_{b,l} < c_{b,r}\}$	[-10.00, 10.00]
								$\{c_{b,r} \mid c_{b,r} > c_{b,l}\}$	[-10.00, 10.00]

Table 4.3: Parameter settings of the actuation backlash identification

The GAASS method has been run ten times using different random seeds and the corresponding results of the identified backlash parameters are shown in Table 4.4. The identified parameter values, denoted with “ $\hat{\cdot}$ ”, are compared using the relative percentage error $\%e_r$ defined earlier in Eq. (3.4). Obviously, parameter values having the lowest $\%e_r$ give the best solutions. Fig. 4.2 depicts the simulated actuator characteristic with the best-identified backlash parameter values ($\hat{m}_b = 1.09$, $\hat{c}_{b,l} = 0.48$, $\hat{c}_{b,r} = 1.02$).

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\%e_r$
0	1.19	1.16	1.81	0.50
1	1.11	0.59	1.15	0.34
2	1.09	0.48	1.02	0.33
3	1.09	0.50	1.08	0.35
4	1.02	-0.05	0.48	0.44
5	1.10	0.55	1.09	0.34
6	1.20	1.20	1.78	0.42
7	1.24	1.45	2.05	0.50
8	1.11	0.65	1.12	0.52
9	1.08	0.40	0.97	0.36
Best	1.09	0.48	1.02	0.33

Table 4.4: Actuation backlash parameters identified using GAASS

Fig. 4.2: Simulated actuator characteristic with the best-identified backlash parameter values

4.1.3 Non-parametric Identification of The Duct Pressure Dynamics

The non-parametric identification of the duct pressure dynamics is performed using the GAASS method illustrated in Fig. 4.3. This part is done experimentally using the pressure transducer measurement $p_{1,m}$ as the actual output.

Fig. 4.3: Non-parametric identification of duct pressure dynamics using the GAASS method

In this duct pressure dynamics identification, the input signal v is the current step given in Eq. (4.1) and the actuator model $\hat{G}$ is given in Eq. (3.26) with the best-identified backlash parameter values ($\hat{m}_b = 1.09$, $\hat{c}_{b,l} = 0.48$, $\hat{c}_{b,r} = 1.02$) from Section 4.1.2. The plant model $\hat{P}$ is described by Eq. (3.31) – (3.32) for the first-order duct pressure dynamics model. Since the input signal is a current step, the simulated output of the plant model $\hat{p}_1$ is therefore given by

$$\hat{p}_1(t, \tau) = p_{1,t \leq 0} + (p_{1,t > 0} - p_{1,t \leq 0}) \left[1 - \exp\left(\frac{-t}{\tau}\right) \right] \quad (4.4)$$

where p_1 is the valve upstream pressure given in Eq. (3.31) – (3.32) and τ is the flow time constant to be identified here. The GAASS method continuously searches for the best value of the flow time constant until the maximum number of generations, $gen = 200$ is reached (stop criterion). The parameter settings of the duct pressure dynamics identification are summarized in Table 4.5.

Sensor Used	GAASS Parameters					Input (v)	Mapping Model	Parameter Set	Search Domain
	N_{pop}	Gen	c/ξ	$pc, llpc, h$	$Pm, llpm, h$				
Pressure transducer	5	200	0.02/0.01	0.5/0.9	0.02/0.1	Step Eq. (4.1)	$\hat{p}_1$ Eq. (4.4)	$\{\tau 0 < \tau < \tau_{max}\}$	[0, 20.00]

Table 4.5: Parameter settings of the duct pressure dynamics identification

The GAASS method has been run ten times using different random seeds and the corresponding results of the identified time constants are shown in Table 4.6. Fig. 4.4 depicts the simulated pressure step response with the best-identified flow time constant ($\hat{\tau} = 1.79$ sec).

Random Seed#	$\hat{\tau}$ [sec]	%e _r
0	1.79	12.67
1	1.79	12.67
2	1.79	12.67
3	1.79	12.67
4	1.79	12.67
5	1.79	12.67
6	1.79	12.67
7	1.79	12.67
8	1.79	12.67
9	1.79	12.67
Best	1.79	12.67

Table 4.6: Flow time constant identified using GAASS

Fig. 4.4: Simulated pressure step response with the best-identified flow time constant

4.1.4 Non-parametric Identification of The Thermistor Flow Sensor Dynamics

The non-parametric identification of the thermistor flow sensor dynamics is performed using the GAASS method illustrated in Fig. 4.5. This part is done experimentally using the thermistor flow sensor measurement W_m as the actual output.

Fig. 4.5: Non-parametric identification of flow sensor dynamics using the GAASS method

In this thermistor flow sensor dynamics identification, the input signal v is the current step given in Eq. (4.2) and the actuator model $\hat{G}$ is given in Eq. (3.26) with the best-identified backlash parameter values ($\hat{m}_b = 1.09$, $\hat{c}_{b,l} = 0.48$, $\hat{c}_{b,r} = 1.02$). The plant

model $\hat{P}$ is described by Eq. (3.30) for the air flow model. Since the thermistor flow sensor has second-order system dynamics, the simulated output $\hat{W}$ corresponds to the input current step is thus given by the following equation in time-domain form as

$$\hat{W}(t, \zeta, \omega_n) = W_{t \leq 0} + (W_{t > 0} - W_{t \leq 0}) \left[1 - \frac{\exp(-\zeta \omega_n t)}{\sqrt{1 - \zeta^2}} \sin \left(\omega_n \sqrt{1 - \zeta^2} t + \tan^{-1} \left(\frac{\sqrt{1 - \zeta^2}}{\zeta} \right) \right) \right] \quad (4.5)$$

where W is the mass flow rate given in Eq. (3.30) while the damping ratio ζ and the natural frequency ω_n are parameters to be identified here. The GAASS method continuously searches for the best values of damping ratio and natural frequency until the maximum number of generations, $gen = 200$ is reached (stop criterion). The parameter settings of the thermistor flow sensor dynamics identification are summarized in Table 4.7.

Sensor Used	GAASS Parameters					Input (v)	Mapping Model	Parameter Set	Search Domain
	$Npop$	gen	$cl\xi$	$pc,l/pc,h$	$pm,l/pm,h$				
Thermistor flow sensor	5	200	0.02/0.02	0.5/0.9	0.02/0.1	Step Eq. (4.2)	$\hat{W}$ Eq. (4.5)	$\{\zeta 0 < \zeta < 1\}$	[0, 0.99]
								$\{\omega_n 0 \leq \omega_n \leq \omega_{max}\}$	[0, 10.00]

Table 4.7: Parameter settings of the thermistor flow sensor dynamics identification

The GAASS method has been run ten times using different random seeds and the corresponding results of the identified damping ratios and natural frequencies are shown in Table 4.8. Fig. 4.6 depicts the simulated flow step response with the best-identified damping ratio and natural frequency ($\hat{\zeta} = 0.50$, $\hat{\omega}_n = 0.22$ rad/s).

Random Seed#	$\hat{\zeta}$	$\hat{\omega}_n$ [rad/s]	%e _r
0	0.51	0.22	2.70
1	0.53	0.23	2.86
2	0.51	0.23	2.70
3	0.52	0.23	2.74
4	0.51	0.23	2.69
5	0.49	0.23	2.70
6	0.50	0.23	2.70
7	0.50	0.22	2.65
8	0.53	0.23	2.83
9	0.57	0.25	3.45
Best	0.50	0.22	2.65

Table 4.8: Thermistor flow sensor dynamics parameters identified using GAASS

Fig. 4.6: Simulated flow step response with the best-identified flow sensor dynamics parameters

4.2 Simulation Results

This section presents the simulation results of the parametric identification of the predefined actuator hysteresis and the actuator hysteresis inverse compensation. Section 4.2.1 shows the simulation results of the predefined actuator hysteresis identification and Section 4.2.2 shows the simulation results of the actuator hysteresis inverse compensation with a sinusoidal function as the control input. A discussion of the simulation results is presented in Section 4.3.

4.2.1 Simulation of The Parametric Identification of The Predefined Actuator Hysteresis

The simulation of the predefined actuator hysteresis identification is performed using the GAASS method depicted in Fig. 4.7. The predefined actuator hysteresis is induced to the actuator via the PC controller.

Fig. 4.7: Simulation of the parametric identification of actuator hysteresis using the GAASS method

In this actuator hysteresis identification, the input signal v is the sinusoidal current command given in Eq. (4.3) while the predefined actuator hysteresis model $\hat{H}$ is a static hysteresis (hysteresis with fixed parameter values) given in Eq. (3.14). The predefined parameter values of $\hat{H}$ are listed in Table 4.9.

Predefined Hysteresis Parameters							
$m_{h,l}$	$m_{h,r}$	$m_{h,t}$	$m_{h,b}$	$c_{h,l}$	$c_{h,r}$	$c_{h,t}$	$c_{h,b}$
1.01	1.05	0.10	0.15	-0.25	0.50	14.00	7.00

Table 4.9: Predefined Hysteresis Parameter Values

The parameters to be identified in this subsection are the system parameters of ψ which consists of the parameters $m_{h,l}$, $m_{h,r}$, $m_{h,t}$, $m_{h,b}$, $c_{h,l}$, $c_{h,r}$, $c_{h,t}$, $c_{h,b}$ in the actuator hysteresis model $\hat{H}$, m_b , $c_{b,l}$, $c_{b,r}$ in the actuator model $\hat{G}$, and τ , ζ , ω_n in the plant model $\hat{P}$. The actuator model $\hat{G}$, and the plant model $\hat{P}$ are given in Eq. (3.26), and Eq. (3.30) – (3.32) respectively whose parameter search domains are estimated from the identification results of Section 4.1.2 – 4.1.4. If the position ($\hat{\theta}$) is used as the system output, the set of parameters to be identified will be the ones in $\hat{G}$ and $\hat{H}$. If the pressure ($\hat{p}_1$) is used as the system output, the set of parameters to be identified will be those in $\hat{G}$, $\hat{P}$ ($\hat{p}_1$), and

$\hat{H}$. If the mass flow rate ($\hat{W}$) is used as the system output, the set of parameters to be identified will be those in $\hat{G}$, $\hat{P}(\hat{W})$, and $\hat{H}$. The GAASS method continuously searches for the best value of the system parameters until the maximum number of generations, $gen = 500$ is reached (stop criterion). The parametric identification of the predefined actuator hysteresis is configured by the settings shown in Table 4.10.

Sensor Type	GAASS Parameters					Input (v)	Mapping Model (ψ)	Parameter Set	Search Domain
	$Npop$	gen	c/ξ	pc,lp,pc,h	pm,lp,pm,h				
Position sensor ¹ , Pressure transducer ² , Thermistor flow sensor ³	10	500	0.009/ 0.05	0.5/0.9	0.01/0.1	Sinusoidal Eq. (4.3)	$\hat{G}^{(1,2,3)}$ Eq. (3.26)	$\{m_b m_b > 0\}$	[0, 5.00]
								$\{c_{b,l} c_{b,l} < c_{b,r}\}$	[-5.00, 5.00]
								$\{c_{b,r} c_{b,r} > c_{b,l}\}$	[-5.00, 5.00]
							$\hat{p}_1^{(2)}$ Eq. (3.32)	$\{\tau 0 < \tau < \tau_{max}\}$	[0, 10.00]
							$\hat{W}^{(3)}$ Eq. (3.36)	$\{\zeta 0 < \zeta < 1\}$	[0, 0.99]
								$\{\omega_n 0 \leq \omega_n \leq \omega_{max}\}$	[0, 5.00]
							$\hat{H}^{(1,2,3)}$ Eq. (3.14)	$\{m_{h,l} m_{h,l} > 0\}$	[0, 5.00]
								$\{m_{h,r} m_{h,r} > 0\}$	[0, 5.00]
								$\{m_{h,l} 0 < m_{h,l} < \min(m_{h,l}, m_{h,r})\}$	[0, 5.00]
								$\{m_{h,b} 0 < m_{h,b} < \min(m_{h,l}, m_{h,r})\}$	[0, 5.00]
								$\{c_{h,l} c_{h,l} < c_{h,r}\}$	[-5.00, 5.00]
								$\{c_{h,r} c_{h,r} > c_{h,l}\}$	[-5.00, 5.00]
								$\{c_{h,l} c_{h,l(\min)} < c_{h,l} < c_{h,l(\max)}\}$	[4.00, 20.00]
								$\{c_{h,b} c_{h,b(\min)} < c_{h,b} < c_{h,b(\max)}\}$	[4.00, 20.00]

Table 4.10: Parameter settings of the predefined actuator hysteresis identification

The GAASS method has been run ten times using different random seeds and the corresponding simulation results of the identified hysteresis parameters using different model outputs are shown in Table 4.11 – 4.13. The simulated output with the predefined hysteresis and the simulated output generated by the identified hysteresis with the average parameter values found using different model outputs are depicted in Fig. 4.8 – 4.12.

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{m}_{k,l}$	$\hat{m}_{k,r}$	$\hat{m}_{k,t}$	$\hat{m}_{k,b}$	$\hat{c}_{k,l}$	$\hat{c}_{k,r}$	$\hat{c}_{k,t}$	$\hat{c}_{k,b}$	%e _r
0	1.15	0.91	0.92	1.10	1.11	0.32	0.31	0.42	0.89	12.57	5.36	1.30
1	1.09	0.24	0.98	1.07	1.08	0.25	0.24	-0.19	0.47	16.73	5.37	1.22
2	1.09	-0.01	0.87	1.05	1.06	0.13	0.44	0.25	0.91	12.97	5.54	1.60
3	1.13	0.02	0.89	1.09	1.11	0.28	0.34	-0.34	0.83	13.84	6.04	1.23
4	1.17	0.89	1.24	1.06	1.11	0.24	0.38	-0.06	0.86	12.08	6.01	1.23
5	1.20	1.28	1.72	1.06	1.08	0.28	0.35	0.42	0.75	12.15	6.11	1.18
6	1.04	0.41	1.21	1.03	1.05	0.20	0.39	-0.02	0.71	15.97	6.29	1.30
7	1.08	1.27	1.69	1.05	1.05	0.14	0.24	0.27	0.41	12.75	5.95	1.27
8	1.15	-0.03	0.82	1.03	1.04	0.18	0.23	0.33	0.42	16.11	5.95	1.17
9	1.11	1.34	1.90	1.02	1.03	0.11	0.17	0.02	0.38	12.13	5.68	1.31
Average	1.12	0.63	1.22	1.06	1.07	0.21	0.30	0.10	0.66	13.80	5.83	1.28

Table 4.11: Simulation result of the actuator hysteresis parameters identified using position model output

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{\tau}$	$\hat{m}_{k,l}$	$\hat{m}_{k,r}$	$\hat{m}_{k,t}$	$\hat{m}_{k,b}$	$\hat{c}_{k,l}$	$\hat{c}_{k,r}$	$\hat{c}_{k,t}$	$\hat{c}_{k,b}$	%e _r
0	1.06	0.49	0.82	1.77	1.12	1.12	0.23	0.37	0.57	0.99	9.24	5.07	3.88
1	1.20	0.05	0.57	1.77	1.05	1.08	0.15	0.21	0.33	0.79	11.56	6.19	2.26
2	1.10	1.01	1.66	1.80	1.16	1.16	0.17	0.36	0.66	1.16	7.76	5.28	3.55
3	1.15	0.34	0.68	1.80	1.14	1.14	0.34	0.38	0.77	1.02	8.24	5.54	3.07
4	1.21	0.15	0.59	1.76	1.14	1.11	0.32	0.39	0.71	1.08	11.24	4.69	3.43
5	1.05	0.55	0.98	1.76	1.09	1.10	0.20	0.24	0.65	0.96	11.31	6.28	2.85
6	1.17	0.70	1.41	1.77	1.01	1.10	0.10	0.11	-0.07	0.87	8.16	5.06	3.22
7	1.09	0.76	1.56	1.78	1.03	1.09	0.24	0.36	-0.05	0.83	11.90	6.03	1.59
8	1.21	1.41	2.02	1.78	1.01	1.09	0.20	0.56	0.28	0.81	9.80	5.57	1.98
9	1.09	1.25	2.01	1.79	1.12	1.11	0.19	0.22	0.57	1.03	9.34	6.81	2.72
Average	1.13	0.67	1.23	1.78	1.09	1.11	0.21	0.32	0.43	0.95	9.86	5.65	2.86

Table 4.12: Simulation result of the actuator hysteresis parameters identified using pressure model output

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{\zeta}$	$\hat{\omega}_n$	$\hat{m}_{k,l}$	$\hat{m}_{k,r}$	$\hat{m}_{k,t}$	$\hat{m}_{k,b}$	$\hat{c}_{k,l}$	$\hat{c}_{k,r}$	$\hat{c}_{k,t}$	$\hat{c}_{k,b}$	%e _r
0	1.04	1.11	1.49	0.55	0.24	0.95	1.06	0.11	0.32	-0.18	0.86	9.95	5.68	4.47
1	1.08	0.04	0.85	0.52	0.22	1.07	1.08	0.15	0.28	-0.04	0.99	8.45	6.42	2.71
2	1.02	1.31	1.95	0.49	0.25	1.09	1.11	0.08	0.14	0.76	1.00	9.53	6.85	1.97
3	1.08	0.34	1.17	0.55	0.23	1.14	1.18	0.14	0.26	0.84	1.43	10.32	6.43	2.27
4	1.04	1.31	1.67	0.49	0.23	1.17	1.23	0.09	0.19	0.90	1.59	11.53	6.69	3.32
5	1.11	0.78	1.29	0.50	0.24	1.13	1.14	0.12	0.25	0.79	1.41	10.94	6.65	1.64
6	1.14	0.56	1.20	0.53	0.24	1.07	1.08	0.04	0.14	-0.17	0.94	10.83	5.93	1.32
7	1.07	1.20	1.60	0.55	0.22	1.03	1.07	0.16	0.33	-0.25	0.98	10.37	6.59	3.05
8	1.22	0.19	1.12	0.49	0.25	1.16	1.19	0.19	0.25	0.10	1.39	8.67	5.59	4.17
9	1.23	0.01	0.76	0.53	0.25	1.04	1.22	0.08	0.12	0.75	1.33	8.42	6.01	4.08
Average	1.10	0.68	1.31	0.52	0.24	1.09	1.14	0.12	0.23	0.35	1.20	9.89	6.28	2.90

Table 4.13: Simulation result of the actuator hysteresis parameters identified using flow model output

Fig. 4.8: Simulated position responses with the predefined hysteresis and the identified hysteresis

Fig. 4.9: Simulated pressure responses with the predefined hysteresis and the identified hysteresis

Fig. 4.10: Simulated flow responses with the predefined hysteresis and the identified hysteresis

Plotting the dimensionless unit output of the actuator versus the dimensionless unit input of the actuator, the actuator hysteresis loop identified using each model output is compared in Fig. 4.11.

Fig. 4.11: Comparison of the identified actuator hysteresis using different model outputs

4.2.2 Simulation of The Actuator Hysteresis Inverse Compensation

The simulation of the actuator hysteresis inverse compensation is performed after the successful identification of the actuator hysteresis parameters in Section 4.2.1. The identified parameter values are applied to the hysteresis inverse model given in Eq. (3.47) to carry out the simulation of the model-based, feed-forward compensation. The flow diagram of the actuator control with hysteresis inverse compensation is depicted in Fig. 4.12.

Fig. 4.12: Simulation of the actuator control with hysteresis inverse compensation

In Fig. 4.12, the hysteresis inverse model H^{-1} derived from the identified hysteresis parameters is cascaded before the predefined hysteresis model $\hat{H}$ prior to sending the signal to control the actuator model $\hat{G}$. Since the predefined actuator hysteresis is static, the hysteresis inverse model with the successfully identified parameter values should be able to compensate the hysteresis effect for any type of control input. Thus, a sinusoidal function which is different from the input used in the hysteresis identification (Eq. (4.3)) is employed here as the control input, u_d , given by

$$u_d(t) = 9.0 + 1.0 \sin\left(\frac{2\pi}{12}\right) \quad [\text{mA}] \quad (4.6)$$

In fact, the sinusoidal input u_d given in Eq. (4.6) is chosen such that its amplitude is always bounded by the maximum and minimum values of Eq. (4.3). This bounded control input minimizes the discrepancy due to inaccurately identified parameter values applied to the hysteresis inverse model. Fig. 4.13 – 4.17 have revealed the effect of the hysteresis inverse compensation method when the input u_d is used to control the actuator for a duration of 60 seconds.

Fig. 4.13: Comparison between the actuator position with hysteresis and with hysteresis inverse compensation whose parameters are identified from the position model output

Fig. 4.14: Comparison between the upstream pressure with hysteresis and with hysteresis inverse compensation whose parameters are identified from the pressure model output

Fig. 4.15: Comparison between the flow rate with hysteresis and with hysteresis inverse compensation whose parameters are identified from the flow model output

The effectiveness of the hysteresis inverse compensation is measured by the average percentage control error, ε_c , defined as the difference between the output governed by the compensated signal and the output governed by the control input signal during the control period. ε_c is given by

$$\% \varepsilon_c = \sqrt{\frac{\sum_{i=1}^n |w_{c,i} - w_{u_d,i}|^2}{\sum_{i=1}^n |w_{u_d,i}|^2}} \times 100\% \quad (4.7)$$

where $w_{c,i}$ denotes the output corresponds to the compensated signal, $w_{u_d,i}$ denotes the output corresponds to the control input signal, and n denotes the total number of data during the control period. The average control error of the hysteresis inverse compensation using each model output is listed in Table 4.14.

Model Used	Control Input (u_d)	Control Period [sec]	% ε_c
Position	Sinusoidal Eq. (4.6)	60	0.28
Pressure			1.29
Flow			0.82

Table 4.14: Average control error of the actuator hysteresis inverse compensation using each model output

4.3 Simulation Results Discussion

The simulation results of the actuator hysteresis parameters identification have shown that the GAASS method successfully identified the predefined actuator hysteresis model. The parameter values identified using position, pressure, and mass flow rate as the system model outputs have all matched the simulated outputs generated by the predefined hysteresis model with an average relative percentage error $\%e_r$ of 1.28, 2.86, and 2.90 respectively. The parameter values found using the position has the lowest $\%e_r$, followed by the values found using the pressure and the mass flow rate. The cause of the higher $\%e_r$ is due to the fact that the outputs of the pressure model and the flow sensor model involve nonlinear functions and system dynamics calculations. Although the average hysteresis parameter values found using position ($\hat{m}_{h,l} = 1.06 \pm 0.05$, $\hat{m}_{h,r} = 1.07 \pm 0.02$, $\hat{m}_{h,t} = 0.21 \pm 0.11$, $\hat{m}_{h,b} = 0.30 \pm 0.15$, $\hat{c}_{h,l} = 0.10 \pm 0.35$, $\hat{c}_{h,r} = 0.66 \pm 0.16$, $\hat{c}_{h,t} = 13.80 \pm 0.20$, $\hat{c}_{h,b} = 5.83 \pm 1.17$), pressure ($\hat{m}_{h,l} = 1.09 \pm 0.08$, $\hat{m}_{h,r} = 1.11 \pm 0.06$, $\hat{m}_{h,t} = 0.21 \pm 0.11$, $\hat{m}_{h,b} = 0.32 \pm 0.17$, $\hat{c}_{h,l} = 0.43 \pm 0.68$, $\hat{c}_{h,r} = 0.95 \pm 0.45$, $\hat{c}_{h,t} = 9.86 \pm 4.14$, $\hat{c}_{h,b} = 5.65 \pm 1.35$), and mass flow rate ($\hat{m}_{h,l} = 1.09 \pm 0.08$, $\hat{m}_{h,r} = 1.14 \pm 0.09$, $\hat{m}_{h,t} = 0.12 \pm 0.02$, $\hat{m}_{h,b} = 0.23 \pm 0.08$, $\hat{c}_{h,l} = 0.35 \pm 0.60$, $\hat{c}_{h,r} = 1.20 \pm 0.70$, $\hat{c}_{h,t} = 9.89 \pm 4.11$, $\hat{c}_{h,b} = 6.28 \pm 0.72$) do not match well with the predefined values, the identified hysteresis loops shown in Fig. 4.11 have been harmonized with the predefined hysteresis model.

The simulation results of the hysteresis inverse compensation shown in Fig. 4.13 – 4.17 have demonstrated its effectiveness revealed by the small percentage control errors $\%\epsilon_c$ range from 0.28 – 1.29. The results have suggested that although the exact hysteresis parameter values cannot be identified, there are multiple optimum values around the global optimum that the GAASS method can always identify and apply to the hysteresis inverse model to provide an effective compensation performance.

From the simulation results, the following conclusions can be drawn:

- I. The GAASS method can be applied to solve discrete, high-dimension, nonlinear, and constrained optimization problems such as actuation backlash

parameters identification, actuator hysteresis parameters identification, and system dynamics identification.

- II. Various system model outputs such as position, pressure, and mass flow rate can all be applied to the GAASS method to perform actuator hysteresis identification.
- III. The search space of the hysteresis parameters identification contains multiple local optima closed to the global optimum, which can be used to model the actuator hysteresis and applied to the hysteresis inverse model to perform effective actuator hysteresis compensation.

CHAPTER 5 EXPERIMENT OF THE HYSTERESIS PARAMETERS IDENTIFICATION AND HYSTERESIS INVERSE COMPENSATION

5.1 Description of The Apparatus

An apparatus has been developed to demonstrate the effectiveness of the proposed hysteresis identification and compensation method using the GAASS in a real application. As illustrated in Fig. 5.1, the apparatus is a pneumatic control system consists of two major parts: a pneumatic pipeline system and a command unit.

Fig. 5.1: Pneumatic system

The pneumatic control system is part of the aircraft engine bleed-air control test rig depicted in Fig. 5.2. The aircraft engine bleed-air control test rig is installed at the Systems and Control Laboratory of Ryerson University. Fig. 5.3 shows a picture of the test rig at the laboratory.

Fig. 5.2: Layout of the aircraft engine bleed-air control test rig

Fig. 5.3: Picture of the aircraft engine bleed-air control test rig

The pneumatic pipeline system consists of a single-stage air compressor, two 180-Gal pressure vessels, a $\frac{3}{4}$ "-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 air flow inside the pneumatic

compressed air of 100 psig at room temperature. The air flow inside the pneumatic pipeline is controlled using a 3/4"-ID brass ball valve driven by an electromechanical actuator manufactured by BI-TORQ, CARBO-BOND, Inc. (Fig. 5.4). Along the pipeline, two sensors are installed. A static pressure transducer manufactured by Omega Instrument, Inc. (Fig. 5.5) is installed upstream of the control valve while a thermistor flow sensor manufactured by Honeywell (Fig. 5.6) is installed downstream of the control valve.

Fig. 5.4: Electromechanical-valve actuator manufactured by BI-TORQ, CARBO-BOND, Inc.

Fig. 5.5: Static pressure transducer manufactured by Omega Instrument, Inc.

Fig. 5.6: Thermistor flow sensor manufactured by Honeywell

The static pressure transducer measures the upstream static pressure while the thermistor flow sensor measures the mass flow rate of air exiting the system. The flow sensor is located in the far end downstream of the control valve and a set of vanes is installed in between the two in order to establish a fully-developed flow condition. The definition of a fully-developed flow is that the acceleration effect (i.e. eddy current) due to the growing of boundary layer has vanished and the flow velocity is purely axial and varies only in the lateral direction. Under this condition, the flow can be assumed as an undisturbed one-dimensional flow, and thus, the flow rate can be measured more accurately.

The command unit consists of a Pentium-III 600-MHz PC, a 16-bit A/D board and a 16-bit D/A board both manufactured by National Instruments, Co. The PC serves as the controller that sends out current command with the induced actuator hysteresis and collects measurements of a valve-opening position sensor, a static pressure transducer, and a thermistor flow sensor.

5.2 Experiment Procedures

The experiment is conducted at a room temperature of about 530 °R and an atmospheric pressure of 14.7 psia. There are three major procedures in the experiment: 1) data acquisition, 2) parametric identification of the predefined actuator hysteresis, and

3) actuator hysteresis inverse compensation. The flow of the procedures is illustrated in Fig. 5.7.

Fig. 5.7: Flow diagram of the actuator hysteresis identification and its inverse compensation

Data acquisition is done by collecting the output signals from a position sensor, a pressure transducer, and a thermistor flow sensor simultaneously through the A/D board. The output signals represent the actuator and the plant responses corresponding to the input signal and the induced hysteresis model. The input signal used for the parametric identification of the actuator hysteresis is defined by Eq. (4.3), whose amplitude is within the control range of the valve actuator and is able to generate measurable output signals. The induced hysteresis model here is the predefined actuator hysteresis, H . H is a static hysteresis which is programmed in the PC and its output is sent out to the actuator via the D/A board.

The actuator hysteresis parameters identification is conducted together with the system parameters identifications of $\hat{G}$, $\hat{p}_1$, and $\hat{W}$ as described in Section 4.2.1. This part is performed subsequently after the data acquisition period.

The actuator hysteresis inverse compensation is performed following the identification of the actuator hysteresis parameters. The identified parameters values are fed to the hysteresis inverse model to carry out the actuator control with the hysteresis feed-forward compensation.

The experiment procedure is started by turning on the upstream manual ball valve at about 20 degrees valve-opening angle. At this valve-opening angle, the total pressure, p_t , is maintained at about 30 psig. Then, the current command is 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 thermistor flow sensor are acquired simultaneously by the PC via the A/D board. The acquired output data are then fed to the GAASS method to

perform the actuator hysteresis identification. Lastly, the successfully identified parameter values of the actuator hysteresis are used to derive the hysteresis inverse model to carry out the hysteresis compensation.

5.3 Experimental Results

5.3.1 Experiment on The Parametric Identification of The Predefined Actuator Hysteresis

The experiment on the parametric identification of the predefined actuator hysteresis is performed using the GAASS method depicted in Fig. 5.8.

Fig. 5.8: Experiment on the parametric identification of actuator hysteresis using the GAASS method

In Fig. 5.8, the input signal, v , is the sinusoidal current command given in Eq. (4.3) while the predefined actuator hysteresis, H , and the hysteresis model, $\hat{H}$, are given in Eq. (3.14). H is programmed in the PC with fixed parameter values given in Table 4.9. The output of H is sent out to the actuator via the D/A board. The actuator model, $\hat{G}$, is given in Eq. (3.26). The plant model, $\hat{P}$, is the mathematical description of the plant, P , described by Eq. (3.30) for the air flow model and Eq. (3.31) – (3.32) for the first-order duct pressure dynamics model. The parameters to be identified in this procedure are the parameters of the actuator hysteresis model $\hat{H}$: $m_{h,l}$, $m_{h,r}$, $m_{h,t}$, $m_{h,b}$, $c_{h,l}$, $c_{h,r}$, $c_{h,t}$, $c_{h,b}$;

parameters of the actuator model $\hat{G}$: m_b , $c_{b,l}$, $c_{b,r}$; parameters of the duct pressure dynamics $\hat{p}_1$: τ , and parameters of the thermistor flow sensor dynamics $\hat{W}$: ζ , ω_n . The GAASS method continuously searches for the best value of the system parameters until the maximum number of generations, $gen = 500$ is reached (stop criterion). The parameter settings are the same as those of the simulation model listed in Table 4.10. The experimental results of the actuator hysteresis identification using various measurements of a position sensor, a pressure transducer, and a thermistor flow sensor are listed in Table 5.1 – 5.3. The actual output with the predefined hysteresis and the simulated output generated by the identified hysteresis model with the average parameter values found using different sensor measurements are depicted in Fig. 5.9 – 5.11.

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{m}_{h,l}$	$\hat{m}_{h,r}$	$\hat{m}_{h,t}$	$\hat{m}_{h,b}$	$\hat{c}_{h,l}$	$\hat{c}_{h,r}$	$\hat{c}_{h,t}$	$\hat{c}_{h,b}$	% e_r
0	1.22	0.53	1.47	1.01	1.03	0.07	0.13	-0.32	0.46	10.62	7.24	2.15
1	1.13	0.26	0.71	1.10	1.10	0.14	0.14	0.14	1.10	9.83	7.16	3.07
2	1.17	-0.05	0.48	1.08	1.10	0.14	0.12	0.15	1.02	11.97	7.33	3.72
3	1.02	0.49	1.01	1.01	1.08	0.08	0.12	-0.28	0.92	10.71	7.20	2.38
4	1.12	0.30	0.86	1.09	1.10	0.10	0.12	0.12	1.10	11.29	7.35	2.93
5	1.09	1.45	2.04	1.09	1.10	0.11	0.10	0.09	1.09	11.06	7.46	2.81
6	1.24	0.22	0.70	1.01	1.09	0.10	0.13	-0.32	1.04	10.36	7.26	2.39
7	1.03	0.79	1.49	1.09	1.10	0.14	0.13	0.13	1.10	11.96	7.21	3.02
8	1.02	0.83	1.52	1.09	1.10	0.14	0.13	0.13	1.10	10.28	7.23	2.98
9	1.11	1.17	1.68	0.99	0.99	0.12	0.12	-0.53	0.12	11.21	7.31	2.71
Average	1.12	0.60	1.20	1.06	1.08	0.11	0.12	-0.07	0.91	10.93	7.28	2.82

Table 5.1: Experimental result of the actuator hysteresis parameters identified using position sensor measurement

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{\tau}$	$\hat{m}_{h,l}$	$\hat{m}_{h,r}$	$\hat{m}_{h,t}$	$\hat{m}_{h,b}$	$\hat{c}_{h,l}$	$\hat{c}_{h,r}$	$\hat{c}_{h,t}$	$\hat{c}_{h,b}$	% e_r
0	1.17	1.02	1.49	1.80	1.09	1.09	0.12	0.11	-0.12	0.86	10.40	7.25	10.60
1	1.21	0.37	0.65	1.76	1.08	1.13	0.12	0.11	-0.11	1.12	9.90	7.23	10.58
2	1.22	0.55	1.30	1.76	1.08	1.11	0.10	0.10	0.11	1.07	10.72	7.34	10.50
3	1.03	0.41	0.72	1.80	1.09	1.12	0.23	0.13	0.17	1.09	10.10	7.15	10.56
4	1.11	0.72	1.49	1.79	1.07	1.12	0.10	0.09	0.11	1.11	10.16	7.45	10.76
5	1.10	1.20	1.82	1.78	1.08	1.07	0.10	0.10	-0.11	0.68	10.46	7.42	10.89
6	1.04	0.59	1.48	1.77	1.13	1.13	0.84	0.07	0.02	1.14	9.90	7.26	10.55
7	1.02	1.34	1.96	1.80	1.09	1.12	0.11	0.11	0.11	1.10	10.35	7.30	10.64
8	1.06	0.42	0.73	1.80	1.09	1.11	0.11	0.11	0.14	1.10	9.66	7.29	10.70
9	1.09	0.53	1.06	1.80	1.09	1.09	0.12	0.11	-0.11	0.95	10.31	7.24	10.88
Average	1.11	0.72	1.27	1.79	1.09	1.11	0.20	0.10	0.02	1.02	10.20	7.29	10.66

Table 5.2: Experimental result of the actuator hysteresis parameters identified using pressure transducer measurement

Random Seed#	$\hat{m}_b$	$\hat{c}_{b,l}$	$\hat{c}_{b,r}$	$\hat{\zeta}$	$\hat{\omega}_n$	$\hat{m}_{h,l}$	$\hat{m}_{h,r}$	$\hat{m}_{h,t}$	$\hat{m}_{h,b}$	$\hat{c}_{h,l}$	$\hat{c}_{h,r}$	$\hat{c}_{h,t}$	$\hat{c}_{h,b}$	%e _r
0	1.14	0.23	1.17	0.49	0.22	1.09	1.10	0.19	0.13	0.17	1.09	10.61	7.32	4.90
1	1.10	0.22	1.27	0.56	0.25	1.10	1.11	0.14	0.13	0.20	1.10	11.15	7.34	5.02
2	1.08	0.01	0.99	0.53	0.22	1.09	1.10	0.12	0.13	-0.17	1.08	11.29	7.33	4.90
3	1.14	0.10	1.36	0.49	0.24	1.08	1.10	0.13	0.13	-0.13	1.09	10.40	7.31	4.88
4	1.06	0.70	0.69	0.56	0.23	1.09	1.10	0.12	0.13	0.13	1.10	11.34	7.32	4.98
5	1.22	0.91	2.01	0.53	0.22	1.09	1.10	0.14	0.14	0.14	1.08	10.53	7.25	4.94
6	1.11	1.12	0.49	0.50	0.23	1.01	1.09	0.10	0.13	-0.32	1.04	10.36	7.26	4.83
7	1.12	0.66	1.35	0.54	0.24	1.08	1.10	0.12	0.12	0.12	1.10	11.67	7.36	4.85
8	1.23	1.26	1.78	0.57	0.25	1.08	1.10	0.14	0.14	-0.14	1.08	10.78	7.23	4.89
9	1.15	1.37	1.74	0.50	0.25	1.08	1.10	0.13	0.12	0.13	1.10	11.11	7.33	4.92
Average	1.14	0.67	1.29	0.53	0.24	1.08	1.10	0.13	0.13	0.01	1.09	10.92	7.31	4.91

Table 5.3: Experimental result of the actuator hysteresis parameters identified using thermistor flow sensor measurement

Fig. 5.9: Actual position sensor measurement with the predefined hysteresis and simulated position model output with the identified hysteresis

Fig. 5.10: Actual pressure transducer measurement with the predefined hysteresis and simulated pressure model output with the identified hysteresis

Fig. 5.11: Actual thermistor flow sensor measurement with the predefined hysteresis and simulated flow model output with the identified hysteresis

Plotting the dimensionless unit output of the actuator versus the dimensionless unit input of the actuator, the actuator hysteresis loop identified using each sensor measurement is compared in Fig. 5.12.

Fig. 5.12: Comparison of the identified actuator hysteresis using different sensor measurements

5.3.2 Experiment on The Actuator Hysteresis Inverse Compensation

The experiment on the actuator hysteresis inverse compensation is performed after the successful identification of the actuator hysteresis parameters in Section 5.3.1. The identified parameter values are applied to the hysteresis inverse model given in Eq. (3.48) to carry out the model-based, feed-forward compensation. The flow diagram of the actuator control with hysteresis inverse compensation is depicted in Fig. 5.13.

Fig. 5.13: Experiment on the actuator control with hysteresis inverse compensation

Since the predefined actuator hysteresis is static, the hysteresis inverse model with the successfully identified parameter values should be able to compensate the hysteresis effect for any type of control input. Thus, in the experiment, a sinusoidal function which is different from the input used in the hysteresis identification (Eq. (4.3)) is employed here as the control input, u_d . This sinusoidal input is given by

$$u_d(t) = 9.0 + 1.0 \sin\left(\frac{2\pi t}{12}\right) \text{ [mA]} \quad (5.1)$$

which has already been defined in Section 4.2.2 for the simulation of the hysteresis inverse compensation. Again, the sinusoidal input u_d given in Eq. (5.1) is chosen such that its amplitude is always bounded by the maximum and minimum values of Eq. (4.3). This bounded control input minimizes the discrepancy due to inaccurately identified parameter values applied to the hysteresis inverse model. Fig. 5.14 – 5.16 have revealed the effect of the hysteresis inverse compensation method when the input u_d is used to control the actuator for a duration of 60 seconds.

Fig. 5.14: Comparison between the actuator position with hysteresis and with hysteresis inverse compensation whose parameters are identified from the position sensor measurement

Fig. 5.15: Comparison between the upstream pressure with hysteresis and with hysteresis inverse compensation whose parameters are identified from the pressure transducer measurement

Fig. 5.16: Comparison between the flow rate with hysteresis and with hysteresis inverse compensation whose parameters are identified from the thermistor flow sensor measurement

The average control error of the hysteresis inverse compensation (as defined in Eq. (4.7)) using each sensor measurement is listed in Table 5.4.

Sensor Used	Control Input (u_d)	Control Period [sec]	% ε_c
Position sensor	Sinusoidal Eq. (5.1)	60	3.80
Pressure transducer			13.27
Thermistor flow sensor			38.87

Table 5.4: Average control error of the actuator hysteresis inverse compensation using each sensor measurement

5.4 Experimental Results Discussion

The experimental results of the actuator hysteresis identification have shown that the predefined hysteresis model has been successfully identified by the GAASS method. As expected, the results have shown that the hysteresis parameters identification using the position sensor measurement yielded the highest accuracy ($\%e_r = 2.82$) compared to the pressure transducer measurement ($\%e_r = 10.66$) and the thermistor flow sensor measurement ($\%e_r = 4.91$) since the position sensor is a direct position measurement and does not contain sensor dynamics. Compared to the simulation results, the relative percentage error $\%e_r$ of the hysteresis parameters identification here are relatively higher because they contain not only the mapping error occurred between the actual system and the system model, but also the sensor measurement errors and the inconsistency of the air supply, aerodynamic disturbance, pipe leakages, etc.

The experimental results of the hysteresis inverse compensation have shown that the effect of hysteresis has been softened when the hysteresis inverse model is cascaded in front of the actuator hysteresis. In fact, as shown in Fig. 5.14, the method works very well in the actuator position control since the effect of hysteresis has almost completely compensated as indicated by the small percentage control error ($\%\varepsilon_c = 3.80$). Since a pressure regulator or a flow regulator is not installed in the pneumatic system, identical flow conditions may not be accomplished at all times in the experiment. Thus, the amplitudes of both the pressure and flow responses shown in Fig. 5.15 and Fig. 5.16 drop as time passes. Hence, the percentage control errors of the pressure control ($\%\varepsilon_c = 13.27$) and the flow control ($\%\varepsilon_c = 38.87$) are definitely higher than the position control. Since

the thermistor flow sensor is the most sensitive device used in our apparatus, a slight change in duct pressure and flow temperature will affect its measurement. Thus, a precise flow control using the raw flow sensor signal is very hard to achieve, and therefore, $\% \varepsilon_c$ of the flow control is the highest in the experiment. 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.

In general, the experimental results have matched the prediction of the simulation results. Among the three sensors used, the measurements from the position sensor and the pressure transducer seem to be more reliable than that from the thermistor flow sensor because both the valve position measurement and the pressure measurement are in agreement with the simulation results. From the experimental results, the following conclusions can be drawn:

- I. The GAASS method can be applied to practical applications such as the pneumatic system used in the experiment.
- II. Position sensor, pressure transducer, and thermistor flow sensor can all be used to perform the actuator hysteresis identification in practical systems. Among the three sensors used, the position sensor and the pressure transducer provide more dependable measurements.
- III. The hysteresis parameters identification using the GAASS method and the hysteresis inverse compensation can be jointly applied to practical applications with the similar complexity as that of the pneumatic system used in the experiment.

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This thesis was concerned with the actuator hysteresis identification using modern stochastic algorithms such as genetic algorithms (GAs). In order to demonstrate the proposed work, a pneumatic system, which was part of an aircraft engine bleed-air test rig was implemented. At the same time, a new adaptive search method, GAASS (Genetic Algorithm with Adaptive Search Space) was proposed. Based on the pneumatic system model, simulations of the actuator hysteresis identification using the GAASS method and the hysteresis inverse compensation were performed. After the simulation results had validated the use of the proposed method, experiments were conducted. The following summarizes the major contributions of this thesis.

In Chapter 1, the general concept of the genetic algorithms was described. The hysteresis encountered in the actuator was stated. The proposed GAASS method and the basic concept of it being applied to the system identification and system inverse compensation were introduced.

In Chapter 2, the structure and mechanisms of the GAASS method were further explained. The effectiveness of the GAASS method was evaluated through the solving of some high-multimodal and high-dimension functions. The convergence performance of the GAASS method was compared with those obtained using the traditional real-coded GA, real-coded Micro-GA and two other recently developed heuristic search techniques used in Adaptive Range Genetic Algorithm (ARGA) and Hybrid Genetic Algorithm Using Local Optimizer Based on Heuristic Pattern Move (*hGA*).

In Chapter 3, the formulation of the actuator hysteresis parameters identification using the GAASS method was described and Krasnosel'skii's hysteron used in the modelling of the actuator hysteresis was introduced. The different sensor measurement methods used to obtain the system output were proposed. Lastly, the hysteresis inverse compensation applied in the actuator control was explained.

In Chapter 4, the configurations of the simulation model were described. The simulation results of the hysteresis parameters identification and hysteresis inverse compensation were shown and discussed.

In Chapter 5, the experiment apparatus and the experiment procedures were described. The experimental results of the hysteresis parameters identification and hysteresis inverse compensation were presented and discussed.

In conclusion, the proposed GAASS approach has efficiently identified optimum solutions in both mathematical models and practical applications of the backlash, hysteresis, as well as system dynamics identification. The simulation results have shown the effectiveness of the GAASS in solving highly multimodal and highly dimensional mathematical problems while the experimental results have demonstrated the ability for the GAASS to handle real engineering applications. The proposed method provides an easy and affordable way to compensate the effect of hysteresis in actuator controls, and it can easily be tailored to compensate other types of system nonlinearities.

6.2 Future Work

Regarding the air flow consistency and the control precision issue, the following future work is recommended:

- 1) Install pressure and/or flow regulator(s) upstream of the control valve in order to provide consistent air supply into the pneumatic system.
- 2) Develop a robust control algorithm for the thermistor flow sensor to reduce the dynamic response and the signal fluctuation such that the flow measurement is more reliable to use.
- 3) Apply an adaptive control scheme which can be incorporated with the hysteresis inverse compensation in order to provide a more accurate and dependable closed-loop control.

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