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Control of input delayed pneumatic vibration isolation table using adaptive fuzzy sliding mode

Abstract

Pneumatic isolators are promising candidates for increasing the quality of accurate instruments. For this purpose, higher performance of such isolators is a prerequisite. In particular, the time-delay due to the air transmission is an inherent issue with pneumatic systems, which needs to be overcome using modern control methods. In this paper an adaptive fuzzy sliding mode controller is proposed to improve the performance of a pneumatic isolator in the low frequency range, i.e., where the passive techniques have obvious shortcomings. The main idea is to combine the adaptive fuzzy controller with adaptive predictor as a new time delay control technique. The adaptive fuzzy sliding mode control and the adaptive fuzzy predictor help to circumvent the input delay and nonlinearities in such isolators. The main advantage of the proposed method is that the closed-loop system stability is guaranteed under certain conditions. Simulation results reveal the effectiveness of the proposed method, compared with other existing time –delay control methods.

Keywords

Pneumatic vibration isolation; transmissibility; AFSMC; input delay; uncertain dynamic system.

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1 INTRODUCTION

Pneumatic vibration isolators (PVIs) are simple and effective vibration isolators. The vibration-sensitive equipment can be isolated using PVIs; for example, for the wafer scanners to fabricate integrated circuits, and the electron microscopes used for submicron imaging (Subrahmanyan and Trumper, 2000). PVIs isolate the vibration properly in the frequency range above the resonance frequencies associated with larger masses with a small stiffness characteristic (Heertjes and van de Wouw, 2006). Due to more precise measurement requirements and the sensitivity of the equipment to vibration, the standards for ground vibration in the frequency range lower than 10 Hz have become tougher (Gordon, 1999). The simultaneous vibration reduction at excitation frequencies above and below the system natural frequencies, which are typically 2-6 Hz, is a hard design constraint. Therefore, the active control of the pneumatic vibration isolation tables was considered as an effective vibration reduction way for the low excitation frequencies (Shin and Kim, 2009).

Previous works on active control of vibration isolators are often based on linear control techniques (Beard et al., 1994; Nagaya and Kanai, 1995). An active/passive nonlinear isolator was proposed which used some optimization techniques (Royston and Singh, 1996). PVI control by combining feedback linearization with a linear loop-shaping controller is adopted (Heertjes and van de Wouw, 2006). The mentioned active control techniques need the measurement of acceleration and not the pressure or mass flow rate (Chen and Shih, 2007). The compensation of the pneumatic isolation table fluctuation which is caused by switching of the feedforward compensator was considered (Shirani et al., 2012). These control methods cannot suppress both the seismic vibration and the direct (payload) disturbances simultaneously. A state space representation of PVIs and a robust time delay control design was presented (Chang et al., 2010). This control algorithm achieved the suppression of seismic vibration and payload disturbance. Many of the existing methods heavily rely on the mathematical model of the plant, while the model of a typical PVI contains many uncertainties and nonlinearities. Therefore, many of such methods cannot guarantee the closed-loop stability under real situations.

In this paper, the adaptive fuzzy sliding mode controller (AFSMC) (Poursamad and Markazi, 2009) is used for the purpose of controlling PVIs. A fuzzy system estimates an ideal sliding-mode controller, and a switching robust controller compensates for the difference between the ideal controller and the fuzzy approximation. The parameters of the fuzzy system and the uncertainty bound of the robust controller, are tuned adaptively. Furthermore, a predictor estimates the future value of the sliding surface parameter. The fuzzy system and adaptive rules use the prediction error to minimize the difference between the estimated value and the actual one in the prediction horizon. The predictor is designed by a one-step-ahead algorithm which reduces the computational cost significantly.

Through this adaptive control algorithm there is no need for known uncertainty bounds of the pneumatic vibration isolator table model, as long as the bound exists. Also, the sliding mode scheme compensates for the uncertainties and disturbances by means of controlling the pressure inside the pneumatic chamber.

The outline of this paper is as follows. 'Problem statement and preliminaries' are provided in Section 2. Section 3 introduces the controller and predictor and investigates the closed-loop stability. Evaluation of the proposed method is considered in Section 4, by simulation studies and comparison to the results of the Time-delay control method introduced in (Shin and Kim, 2009). Concluding Remarks are given in Section 5.

2 PROBLEM STATEMENT AND PRELIMINARIES

2.1 Mathematical modeling of the PVIT

Consider a pneumatic vibration isolation system consisting of a payload and a single pneumatic chamber as shown in Figure 1. Stiffness of the single chamber is known to be dependent on frequency and amplitude of vibration (Lee and Kim, 2007).

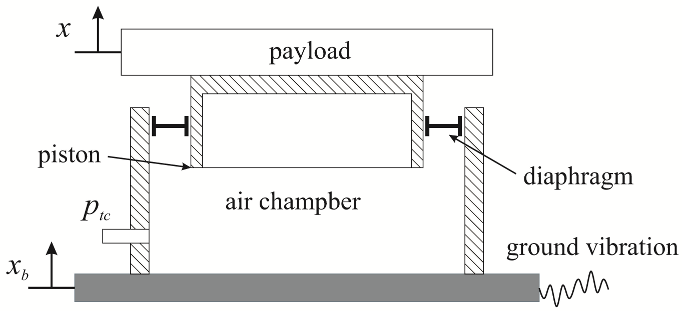

Figure 1: Pneumatic table for isolation of equipment from excitation at ground.

The governing equation for the mentioned pneumatic vibration isolation table can be written in the state space form as

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\dfrac{k_s + k_d}{m} & -\dfrac{c_d}{m} \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{1}{m} \end{bmatrix} \left[\left(k_s + k_d \right) x_b + c_d \dot{x}_b \right] + \begin{bmatrix} 0 \\ \dfrac{A_p}{m} \end{bmatrix} p_{tc}, \tag{1}$$

where, $\boldsymbol{x} = \begin{bmatrix} x & \dot{x} \end{bmatrix}$ is the state vector which consists of the payload vertical movement and velocity. The payload is attached to the base by means of PVI, but the table is disturbed by the base movement $\boldsymbol{x}_b = \begin{bmatrix} x_b & \dot{x}_b \end{bmatrix}$, so the second term in the right hand side of (1) represent the ground vibration effects. p_{tc} is the dynamic pressure from the actuator as the control input of system. Also, m denotes the mass of payload, $k_s = \kappa p_0 A_p^2 / V_{t0}$ real stiffness of the single chamber, k_d and c_d is real part of the complex stiffness of diaphragm and equivalent viscous damping of diaphragm, respectively. A_p is the effective area of the piston cross-sectional area and the diaphragm (Shin and Kim, 2009; Lee and Kim, 2007). Table 1 gives the values of the parameters of mentioned system. It should be noted here that the actuators and sensors which is used for controlling such systems, have some time delays (Chang et al., 2010). This problem gets more importance when high precision of the installed equipment on PVIT is required. Therefore, it is considered that p_{tc} reaches the plant with a time delay τ, as a common way for modeling of the mentioned actuation and measurement delays (Galambos et al., 2014).

Symbol	Name	Value
m	Payload	87 kg
κ	Specific heat ratio	1.4
p_0	Static pressure	$3.51{\times}10^5$ Pa
V_{t0}	Chamber volume	$2.978{\times}10^{-4}$ m^3
A_p	Effective piston area	$2.518{\times}10^{-3}$ m^2
c_d	Equivalent viscous damping of diaphragm	$2.78{\times}10^2$ N.s/m
k_d	Real part of complex stiffness of diaphragm	$1.12{\times}10^4$ N.s/m

Table 1: Parameters of pneumatic spring and payload.

2.2 General problem statement

For the time delay control of PVIs, the general problem can be considered as the following input-delayed nonlinear system as

$$\begin{cases} x^{(n)}(t) = f(\boldsymbol{x}) + g(\boldsymbol{x})\, u(t-\tau) \\ y(t) = C\boldsymbol{x} \end{cases} \tag{2}$$

where $\boldsymbol{x} = [x_1, x_1, \ldots, x_n]^T \in \mathbb{R}^n$, $y(t) \in \mathbb{R}$ and $u(t) \in \mathbb{R}$ are the system states, measurable output and input, respectively, $f(\cdot)$ and $g(\cdot)$ are probably unknown but smooth nonlinear functions, and τ is a constant delay. The control goal is that $u(t)$ causes the system tracks a desired state vector $\boldsymbol{x}_d(t)$ and closed-loop signals remain bounded. It is mentioned that the proposed control design method can be used for nonlinear affine-in-control systems and it is not limited to the SISO systems.

For the adaptive fuzzy sliding mode control (AFSMC) in contrast with time delay control techniques (TDC) (Heertjes and van de Wouw, 2006; Shin and Kim, 2009; Lee and Kim, 2007), there is no need for precise model and the availability of all states. In the so called TDC techniques the delayed value of dynamics $f(\boldsymbol{x}, t-\tau)$ and $g(\boldsymbol{x}, t-\tau)$ are used to approximate the control signal $u(t)$, where τ is an overall time delay. Thus, the input time delay must be considered for controlling the PVIs, and the control problem is changed to an input delay system. The proposed AFSMC with adaptive fuzzy predictor which are introduced in the next section, can enhance the performance of PVIs by solving this control problem.

In this paper, the following single output linear parameter fuzzy system is employed to approximate the nonlinear function and input signal over a compact set X with input $\boldsymbol{x} = [x_1 \ \cdots \ x_n]$, and n_r IF-THEN rules; for example,

Rule r : IF x_1 is A_1^r and ... and x_n is A_n^r THEN $f(\boldsymbol{x}) = k_r$, $r = 1, \ldots, n_r$,

where f is the output of the fuzzy system, k_r is the fuzzy singleton for output of rth rule, and $A_1^r, \ldots, A_n^r$ are the fuzzy sets defined through some Gaussian membership functions as

$$\mu_{A_j^r}(x_j) = \exp\left[-\left(\frac{x_j - c_j^r}{\sigma_j^r}\right)^2\right] \tag{3}$$

in which c_j^r and σ_j^r are the center and width of the Gaussian membership function. Define the firing strength of the rth rule as

$$w_r = \frac{\prod_{j=1}^{n_i} \mu_{A_j^r}(x_j)}{\sum_{r=1}^{n_r} \prod_{i=1}^{n_i} \mu_{A_i^r}(x_i)} \tag{4}$$

and using singleton fuzzification, product inference system, and center average deffuzification, the output of the fuzzy algorithms yield as

$$f(\boldsymbol{x}) = \boldsymbol{k}^{*T}\boldsymbol{w}(\boldsymbol{x}) + \varepsilon \text{ , } \forall \boldsymbol{x} \in X \subset \mathbb{R}^n \tag{5}$$

where $\boldsymbol{k}^* = \left[k_1^*,\ldots,k_{n_r}^*\right]^T \in \mathbb{R}^{n_r}$ is the bounded vector of output fuzzy singleton and $\varepsilon \in \mathbb{R}$ is a bounded error, i.e., $\boldsymbol{k}^* \le \boldsymbol{k}_N$, $\varepsilon \le \varepsilon_N$ with $\boldsymbol{k}_N$ and ε_N being positive constants. $\boldsymbol{w}(\boldsymbol{x}) = \left[w_1(\boldsymbol{x}),\ldots,w_{n_r}(\boldsymbol{x})\right]^T$ is the vectors of firing strength of rules.

Remark 1. *The fuzzy system* (5) *uniformly approximates* $f: X \to Y$ *if* X *is compact (closed and bounded) and* f *is continuous. Then, the approximation error uniformly converges to zero, thus* ε *is a bounded error* (Kosko, 1994).

3 PREDICTOR AND CONTROLLER DESIGN

3.1 Adaptive Fuzzy Predictor (AFP)

The first step is developing an adaptive predictor for system (2). Select positive parameters $a_1,\ldots,a_n$ an appropriately such that the polynomial $s^n + a_n s^{n-1} + \ldots + a_1$ is Hurwitz, then the following matrix A is stable and select the symmetric positive definite matrices P and Q such that the Lyapunov matrix equations $A^T P + PA = -Q$ and $PB = C^T$ are satisfied.

$$A = \begin{bmatrix} 0 & 1 & 0 & \ldots & 0 \\ 0 & 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \ldots & 1 \\ -a_1 & -a_2 & -a_3 & \ldots & -a_n \end{bmatrix},\ B = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix},\ C = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{bmatrix}^T \tag{6}$$

The unknown nonlinear functions $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ can be approximated using the fuzzy systems with input $\hat{\boldsymbol{x}}(t)$, the predictor state vector. According to (5), the output of fuzzy algorithms yield as

$$f_{fuz} = \boldsymbol{h}^{*T}\boldsymbol{w}_{\mathrm{f}} + \varepsilon_f \tag{7}$$

$$g_{fuz} = \boldsymbol{q}^{*T}\boldsymbol{w}_{\mathrm{g}} + \varepsilon_g \tag{8}$$

over a compact set, where $\boldsymbol{h} = [h_1,\ldots,h_{m_r}]^T$ and $\boldsymbol{q} = [q_1,\ldots,q_{m_r}]^T$ are the vectors of output fuzzy singleton, $\boldsymbol{w}_f = [w_{f1},\ldots,w_{fm_r}]^T$ and $\boldsymbol{w}_g = [w_{g1},\ldots,w_{gm_r}]^T$ are the vectors of firing strength of rules.

The nonlinear system (2) with input delay, can be considered as follows

$$\begin{cases} x_i(t) = \dot{x}_{i-1} \quad ; \ i = 1,\ldots,n-1 \\ x_n(t) = f(\boldsymbol{x}) + g(\boldsymbol{x})\, u(t-\tau) \\ y = C\,\boldsymbol{x} \end{cases} \tag{9}$$

where $\boldsymbol{x} = \left[x_1, x_1,\ldots,x_n\right]^T \in \mathbb{R}^n$ is the state vector of system (2).

Regarding the fact that the fuzzy output vectors $\boldsymbol{h}$ and $\boldsymbol{q}$ contain the behavior of system dynamics, the following online predictor can be designed by appropriate adaptation algorithm.

$$\begin{cases} \dot{\boldsymbol{x}}_p\left(t+\tau \mid t\right) = A\boldsymbol{x}_p\left(t+\tau \mid t\right) + B\left[\hat{\boldsymbol{h}}^T\boldsymbol{w}_f\left(t+\tau \mid t\right) + \hat{\boldsymbol{q}}^T\boldsymbol{w}_g\left(t+\tau \mid t\right)u\left(t\right)\right] \\ y_p\left(t+\tau \mid t\right) = C\boldsymbol{x}_p\left(t+\tau \mid t\right) \end{cases} \tag{10}$$

where $\boldsymbol{x}_p\left(t+\tau \mid t\right) = \left[x_{1p}\left(t+\tau \mid t\right),\ldots,x_{np}\left(t+\tau \mid t\right)\right] \in \mathbb{R}^n$ and $y_p\left(t+\tau \mid t\right) \in \mathbb{R}$ are the predictions of the future system states and output of (9) respectively. The following adaptation algorithm is employed to update the fuzzy output vectors

$$\begin{cases} \dot{\hat{\boldsymbol{h}}}\left(t+\tau \mid t\right) = \gamma_1\left[\tilde{y}_p\left(t+\tau \mid t\right)\boldsymbol{w}_f\left(t+\tau \mid t\right) - \mu_1\hat{\boldsymbol{h}}\left(t+\tau \mid t\right)\right] \\ \dot{\hat{\boldsymbol{q}}}\left(t+\tau \mid t\right) = \gamma_2\left[\tilde{y}_p\left(t+\tau \mid t\right)\boldsymbol{w}_g\left(t+\tau \mid t\right) - \mu_2\hat{\boldsymbol{q}}\left(t+\tau \mid t\right)\right] \end{cases} \tag{11}$$

where $\gamma_i = \gamma_i^T > 0,\ i = 1{,}2$ are adaptation rates, $\mu_i > 0$ are modification parameters, and $\tilde{y}_p = y - y_p$ is the predictor output error.

The prediction error dynamics is obtained by subtracting (10) from (9) as

$$\tilde{\boldsymbol{x}}_p\left(t+\tau\right) = \boldsymbol{x}\left(t+\tau\right) - \boldsymbol{x}_p\left(t+\tau \mid t\right) \tag{12}$$

$$\begin{cases} \dot{\tilde{\boldsymbol{x}}}_p\left(t+\tau\right) = A\tilde{\boldsymbol{x}}_p\left(t+\tau\right) + B\left[\tilde{\boldsymbol{h}}^T\boldsymbol{w}_f\left(t+\tau \mid t\right) + \tilde{\boldsymbol{q}}\,\boldsymbol{w}_g\left(t+\tau \mid t\right)u\left(t\right) + \varepsilon\right] \\ \tilde{y}_p\left(t+\tau\right) = C\tilde{\boldsymbol{x}}_p\left(t+\tau\right) \end{cases} \tag{13}$$

where approximation and the overall error $\tilde{\boldsymbol{h}}$, $\tilde{\boldsymbol{q}}$, and ε are defined as

$$\tilde{\boldsymbol{h}} = \boldsymbol{h}^* - \hat{\boldsymbol{h}} \tag{14}$$

$$\tilde{\boldsymbol{q}} = \boldsymbol{q}^* - \hat{\boldsymbol{q}} \tag{15}$$

$$\varepsilon = \boldsymbol{h}^{*T}\left[\boldsymbol{w}_f\left(t+\tau\right) - \boldsymbol{w}_f\left(t+\tau \mid t\right)\right] + \varepsilon_f + \boldsymbol{q}^{*T}\left[\boldsymbol{w}_g\left(t+\tau\right) - \boldsymbol{w}_g\left(t+\tau \mid t\right) + \varepsilon_g\right]u\left(t\right) \tag{16}$$

Remark 2. *It is stated that the fuzzy estimation error is bounded and converges to zero in* Remark (1)*, i.e.,* ε_f *and* ε_g *are bounded. The optimum values of fuzzy inputs are not infinity, thus,* $\boldsymbol{h}^*$ *and* $\boldsymbol{q}^*$ *are bounded. Also,* $\boldsymbol{w}\left(\cdot\right)$ *is bounded based on the definition in* (4)*. Finally, it is concluded that* ε *is a bounded error. So that* $\left|\varepsilon\right| \le \varepsilon_N$ *holds with* ε_N *being a positive constant. Then the following lemma is achieved.*

Lemma 1. *Consider nonlinear system* (2)*, the adaptive fuzzy predictor is given in* (10) *with the adaptive law* (11)*, then the predictor error* $\tilde{\boldsymbol{x}}_p$ *and the fuzzy output vector errors* $\tilde{\boldsymbol{h}}$ *and* $\tilde{\boldsymbol{q}}$ *are uniformly ultimately bounded.*

Proof. Select the Lyapunov candidate function for predictor as

$$V_p\left(\tilde{\boldsymbol{x}}_p\left(t+\tau\right),\tilde{\boldsymbol{h}},\tilde{\boldsymbol{q}}\right)=\frac{1}{2}\tilde{\boldsymbol{x}}_p^T P\,\tilde{\boldsymbol{x}}_p+\frac{1}{2\gamma_1}\tilde{\boldsymbol{h}}^T\tilde{\boldsymbol{h}}+\frac{1}{2\gamma_2}\tilde{\boldsymbol{q}}^T\tilde{\boldsymbol{q}} \tag{17}$$

$$\dot{V}_p=-\frac{1}{2}\tilde{\boldsymbol{x}}_p^T Q\,\tilde{\boldsymbol{x}}_p+\tilde{y}_p\left[\tilde{\boldsymbol{h}}^T\boldsymbol{w}_f\left(t+\tau\mid t\right)+\tilde{\boldsymbol{q}}^T\boldsymbol{w}_g\left(t+\tau\mid t\right)u\left(t\right)+\varepsilon\right]+\frac{1}{\gamma_1}\tilde{\boldsymbol{h}}^T\dot{\tilde{\boldsymbol{h}}}+\frac{1}{\gamma_2}\tilde{\boldsymbol{q}}^T\dot{\tilde{\boldsymbol{q}}}$$

From the predictor adaptation algorithm (11) it can be concluded that

$$\Rightarrow\dot{V}_p=-\frac{1}{2}\tilde{\boldsymbol{x}}_p^T Q\,\tilde{\boldsymbol{x}}_p+\mu_1\tilde{\boldsymbol{h}}^T\hat{\boldsymbol{h}}+\mu_2\tilde{\boldsymbol{q}}^T\hat{\boldsymbol{q}}+\tilde{y}_p\varepsilon$$

By using Young's inequality $b\le\left(a^2+k_1^2b^2\right)\big/2k_1,\ k_1>0$

$$\tilde{y}_p\varepsilon\le\frac{k_1}{2}\tilde{\boldsymbol{x}}_p+\frac{1}{2k_1}\varepsilon_N^2$$

$$\tilde{K}_i^T\hat{K}_i=\tilde{K}_i^T\left(K_i^*-\tilde{K}_i\right)\le-\frac{1}{2}\tilde{K}_i+\frac{1}{2}K_i^{*2}\quad,\quad\tilde{K}_i=\tilde{\mathrm{h}},\tilde{\mathrm{q}}$$

$$\Rightarrow\dot{V}_p\le-\frac{1}{2}\left(\lambda_m\left(Q\right)-k_1\right)\tilde{\boldsymbol{x}}_p-\frac{\mu_1}{2}\tilde{\boldsymbol{h}}-\frac{\mu_2}{2}\tilde{\boldsymbol{q}}+\frac{\mu_1}{2}\boldsymbol{h}^{*2}+\frac{\mu_2}{2}\boldsymbol{q}^{*2}+\frac{1}{2k_1}\varepsilon_N^2\le-\eta_1V_p+\zeta_1$$

$$\eta_1=\min\left\{\frac{\left(\lambda_m\left(Q\right)-k_1\right)}{\lambda_m\left(P\right)},\mu_1\gamma_1,\mu_2\gamma_2\right\}>0\ \text{and const.}$$

$$\zeta_1=\frac{1}{2}\left(\mu_1\boldsymbol{h}^{*2}+\mu_2\boldsymbol{q}^{*2}+\frac{1}{k_1}\varepsilon_N^2\right)>0$$

After selecting the appropriate parameters for the predictor, it can be shown that $-\eta_1V_p+\zeta_1\le 0$ for all $\tilde{\boldsymbol{x}}_p\left(t\right)$ within a compact set X_p, then the time derivative of Lyapunov function of predictor is negative semi-definite. Also, because the input delay does not affect the stability proof of predictor, there is no need to use the stability analysis for time-varying system for it. Thus, $\tilde{\boldsymbol{x}}_p$ and the fuzzy output vector errors $\tilde{\boldsymbol{h}}$ and $\tilde{\boldsymbol{q}}$ are uniformly ultimately bounded.

3.2 Adaptive Fuzzy Sliding Mode Controller (AFSMC)

The prediction of future system states $\boldsymbol{x}_p\left(t+\tau\mid t\right)$ are derived based on the current system information from predictor (10). Now, sliding mode control based on states $\boldsymbol{x}_p\left(t+\tau\mid t\right)$ compensates the effect of input delay in the feedback loop. In this section, a sliding mode feedback control is designed for tracking of reference signal and the overall closed-loop stability.

Consider the fuzzy systems with input $\hat{s}\left(t+\tau\mid t\right)$, which is obtained as

$$\hat{s}\left(t+\tau\mid t\right)=\left(D+\lambda\right)^{n-1}\hat{\tilde{\boldsymbol{x}}}\left(t+\tau\mid t\right) \tag{18}$$

$$\hat{\tilde{\boldsymbol{x}}}\left(t+\tau\mid t\right)=\boldsymbol{x}_d\left(t+\tau\right)-\boldsymbol{x}_p\left(t+\tau\mid t\right) \tag{19}$$

where $\hat{\tilde{\boldsymbol{x}}}\left(t+\tau\mid t\right)$ is the predicted value of $\tilde{\boldsymbol{x}}\left(t\right)$. Based on (5) we have

$$u_{fuz} = \boldsymbol{k}^T \boldsymbol{w} \tag{20}$$

where $\boldsymbol{k} = \left[k_1,\ldots,k_{n_r}\right]^T$ is the vector of output fuzzy singleton, and $\boldsymbol{w} = \left[w_1,\ldots,w_{n_r}\right]^T$ is the vector of firing strength of rules. The estimation error of the fuzzy system is denoted by which is assumed to be bounded, i.e.,

$$\left|\psi\right| < \Psi \tag{21}$$

where Ψ is estimation error bound. An adaptive algorithm is used for tuning the fuzzy singleton output as

$$\dot{\hat{\boldsymbol{k}}} = -\dot{\tilde{\boldsymbol{k}}} = \alpha_1 \hat{s}\left(t+\tau \mid t\right)\boldsymbol{w}\,\mathrm{sgn}\left(g\right) \tag{22}$$

where α_1 is adaptation rate and $\hat{\boldsymbol{k}}$ is the estimated value of output fuzzy singleton, and

$$\tilde{\boldsymbol{k}} = \boldsymbol{k} - \hat{\boldsymbol{k}} \tag{23}$$

Therefore, the output of fuzzy system can be rewritten as

$$\hat{u}_{fuz} = \hat{\boldsymbol{k}}^T \boldsymbol{w} \tag{24}$$

To compensate the fuzzy estimation error, the u_{rb} is designed as

$$u_{rb} = \hat{\Psi}\,\mathrm{sgn}\left[\hat{s}\left(t+\tau \mid t\right)\right]\mathrm{sgn}\left(g\right) \tag{25}$$

where $\hat{\Psi}$ is the error bound estimation which is adjusted adaptively by

$$\dot{\hat{\Psi}} = -\dot{\tilde{\Psi}} = \alpha_2 \left|\hat{s}\left(t+\tau \mid t\right)\right| \tag{26}$$

where α_2 is a positive constant which is defined by designer and

$$\tilde{\Psi} = \Psi - \hat{\Psi} \tag{27}$$

The total control signal consist of both fuzzy and robust control as

$$u = \hat{u}_{fuz} + u_{rb} \tag{28}$$

Lemma 2. *Consider nonlinear time-delay system* (2), *the predictor* (10) *with the update law* (11) *and the adaptive fuzzy sliding mode controller* (28) *with the adaptive law* (22) *and* (26), *then*
(1) All signals in the closed-loop system are bounded.

(2) The tracking error $\tilde{\boldsymbol{x}}$ and the fuzzy estimation errors $\tilde{\boldsymbol{k}}$ and $\tilde{\Psi}$ are uniformly ultimately bounded.

Proof. Select the Lyapunov candidate function for the controller as

$$V_c = \frac{1}{2}s^2 + \frac{|g|}{2\alpha_1}\tilde{\boldsymbol{k}}^T\tilde{\boldsymbol{k}} + \frac{|g|}{2\alpha_2}\tilde{\Psi}^2 \tag{29}$$

For delay compensation the sliding surface is constructed as shown in (18). Remembering that the final goal is to make actual sliding surface of system zero,

$$s(t) = (D+\lambda)^{n-1}\tilde{x}(t) \tag{30}$$

and

$$\tilde{x}(t) = x_d(t) - x(t) \tag{31}$$

From (2), (28), (30), and (31) the derivative of sliding surface derived as

$$\dot{s} = \left(D^n + \sum_{i=1}^{n-1} C_i^{n-1} D^{n-i}\lambda^i\right)\tilde{x} = g(\mathbf{x})\left[u^* - \hat{u}_{fuz}(s,\hat{\mathrm{k}}) - u_{rb}(s,\hat{\Psi})\right] \tag{32}$$

The time derivative of Lyapunov function (29) is

$$\dot{V}_c = g\tilde{\boldsymbol{k}}^T\left(s\boldsymbol{w} + \frac{1}{\alpha_1}\dot{\tilde{\boldsymbol{k}}}\,\mathrm{sgn}(g)\right) + s.g(\psi - u_{rb}) + \frac{|g|}{\alpha_2}\tilde{\Psi}\dot{\tilde{\Psi}}\,.$$

By using (22), (26), and (28) in the derivative we have

$$\dot{V}_c = sg\psi + g\tilde{\boldsymbol{k}}^T\boldsymbol{w}\left(s - \hat{s}(t+\tau \mid t)\right) - s|g|\hat{\Psi}\,\mathrm{sgn}\left[\hat{s}(t+\tau \mid t)\right] - |g|\left|\hat{s}(t+\tau \mid t)\right|\tilde{\Psi} \tag{33}$$

Based on Lemma 1, the predictor error will be bounded as last, thus

$$\lim_{0\ll t}\tilde{\boldsymbol{x}}_p(t+\tau) = 0 \Rightarrow \lim_{0\ll t}\boldsymbol{x}(t+\tau) = \boldsymbol{x}_p(t+\tau \mid t)$$

By using the later result and (18), (19), (30), and (31) it concluded that

$$\lim_{0\ll t} s(t+\tau) = \hat{s}(t+\tau \mid t) \tag{34}$$

Based on the results of (33) and (34), the derivative is simplified as

$$\dot{V}_c = sg\psi - |s||g|\hat{\Psi} - |g||s|(\Psi - \hat{\Psi}) = s.g\psi - |s||g|\Psi \le |s||g||\psi| - |s||g|\Psi$$
$$\Rightarrow \dot{V}_c = -|s||g|(\Psi - |\psi|) \le 0 \tag{35}$$

$\dot{V}_c$ is semi-negative definite then the system is stable and s, $\tilde{\boldsymbol{k}}$, and $\tilde{\Psi}$ will remain bounded. Now consider the following Lipchitz function

$$\Gamma(t) \equiv |s||g|(|\psi| - \Psi) \le -\dot{V}_C \tag{36}$$

From integrating $\Gamma(t)$ it can be shown that

$$\int_0^t \Gamma(\tau)\mathrm{d}\tau \le V_C\left(s(0), \tilde{\boldsymbol{k}}, \tilde{\Psi}\right) - V_C\left(s(t), \tilde{\boldsymbol{k}}, \tilde{\Psi}\right)$$

because $V_C\left(s(0), \tilde{\boldsymbol{k}}, \tilde{\Psi}\right)$ is bounded and $V_C\left(s(t), \tilde{\boldsymbol{k}}, \tilde{\Psi}\right)$ is non-increasing and bounded, therefore

$$\lim_{t\to\infty}\int_0^t \Gamma(\tau)\mathrm{d}\tau \le \infty$$

also, by using the Barbalat Lemma, it is concluded that $\lim_{t\to\infty}\Gamma(t) = 0$ and $\lim_{t\to\infty}s(t) = 0$. Finally it is proved that all signals in the closed loop system will remain bounded and the tracking error is uniformly ultimately bounded.

4 SIMULATION STUDY

The proposed AFSMC-AFP consists of a predictor (10) and a sliding mode controller (28). Figure 2 depicts the block diagram of the control algorithm for the general form of Pneumatic Vibration Isolation Tables (PVITs). The simulation is done by using the control algorithm for the system (1), where $u(t) = p_{tc}$ is input signal. The control command is sent to an electrical drive board which provides the reference voltage for the control servo valve, a proportional valve of nozzle-flapper type (Chang et al., 2010). The valve regulates the dynamic pressure of the chamber. But this actuation process causes an input time delay $\tau = 0.01$ s.

In order to apply the AFSMC, the desired state vector is $\boldsymbol{x}_d(t) = \mathbf{0}$ and the sliding surface is defined as

$$s = \dot{\tilde{x}} + \lambda\tilde{x} \tag{37}$$

In the simulation, the input membership functions are Gaussian. The initial fuzzy output vector are arbitrarily to select as $\hat{\mathrm{k}} = \begin{bmatrix}-0.5 & 0 & 0.5\end{bmatrix}^T$ and the initial value of uncertainty bound is chosen as $\hat{\Psi} = 0.05$. The adaptation rate are set to $\alpha_1 = 0.1$ and $\alpha_2 = 1$. The predictor parameters are selected as $a_1 = 5$, $a_2 = 5$, and the learning gains are specified as $\gamma_1 = 50$ and $\mu_1 = 0.05$. It is noted that the adaptation rate can be tuned based on the size of delay to achieve the good performance.

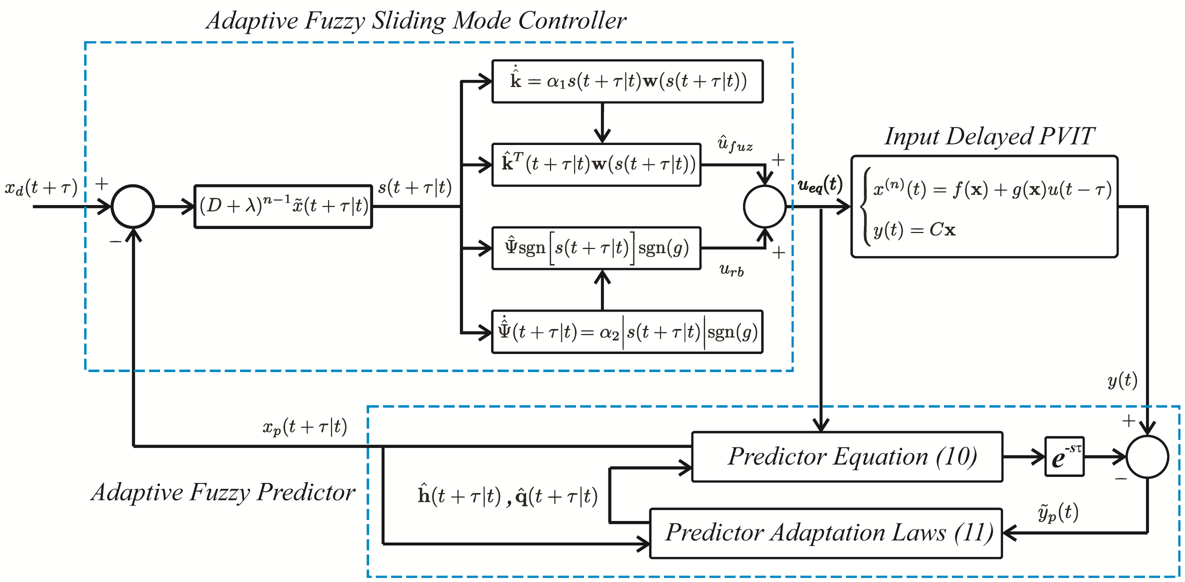

Figure 2: Schematic diagram for proposed AFSMC-AFP.

In this study, a random ground vibration with rate of $\dot{x}_b = 30$ mm/s$_{\text{rms}}$ is used as the base excitation. This excitation is the criteria VC-C in standard of ground vibration (Gordon, 1999) and is allowed marginally for electron microscopes. The system parameters are as in Table 1 for the simulation. The time responses of system are presented in Figures 3 and 4, and the control signal in Figure 5. It is noted that the AFSMC-AFP starts at $t = 20$ s for better understanding. The ratio of cross-and auto- correlation of the vibration signals at the payload is a common index for determining the isolation performance. This index is called transmissibility which is estimated from the two signals as follows

$$Transmissibility = \frac{G_{BX}}{G_{BB}} \tag{38}$$

where the subscripts B and X denote the vibration signals at the base and on the payload, respectively, G_{BX} and G_{BB} cross- and auto-power spectral density function, respectively. For the calculation of this index Hanning window is applied by ensemble average of 50 times, and at a frequency resolution of 0.2 Hz. Figure 6 shows the transmissibility index and isolation performance by the AFSMC-AFP can be better than the TDC technique and the passive one. The root mean square of the transmissibilities by the AFSMC-AFP is less than 40 % of TDC and 2 % of that by the passive one in the frequency range under 7 Hz which is very desirable for enhancing the vibration isolation performance of table for low frequency around the resonance.

Simultaneous suppression was analyzed with seismic vibration and direct disturbance being applied to system. The seismic disturbance was generated in the same way as before, but this time a direct disturbance is applied at $t = 20$ s. Figure 7 shows the time response of the payload resulting from seismic vibration and direct disturbance. Based on this figure and the existing results (Chang et al., 2010), the settling time of the PVI with AFSMC-AFP is significantly less than that of the passive PVI (3.10 s) and less than 50% of TDC (0.99 s). So that based on these results it is evident that the AFSMC-AFP is an effective control scheme for PVIT in simultaneous suppression.

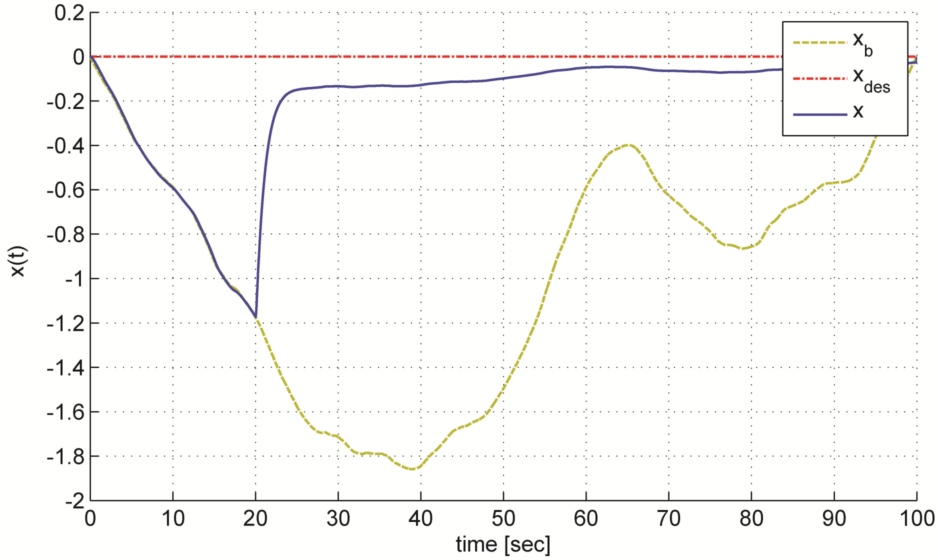

Figure 3: Normalized System position response to seismic vibration VC-C ground vibration ($\tau = 0.01$s).

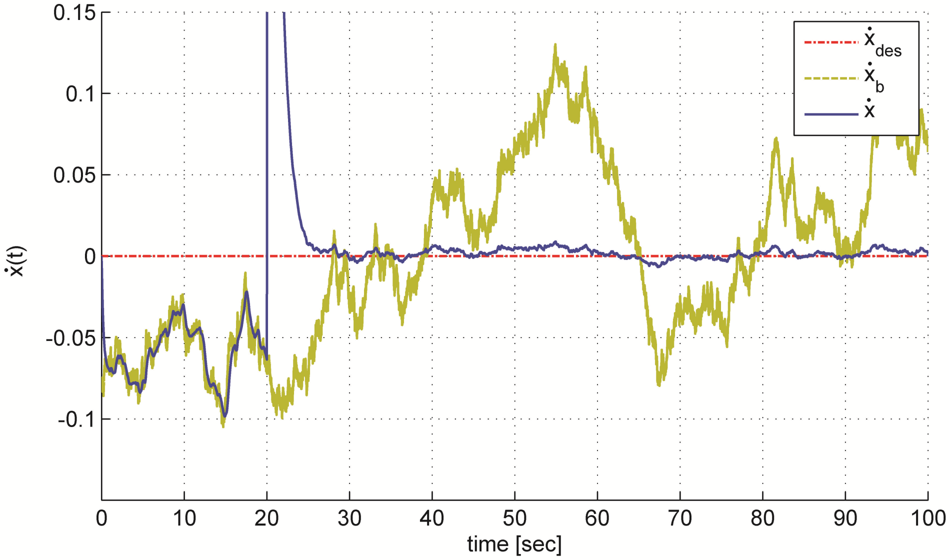

Figure 4: Normalized System velocity response to seismic vibration VC-C ground vibration ($\tau = 0.01$s).

	Frequency Range	Passive	TDC	AFSMC
Root means square (RMS)	1 – 10 Hz	2.8345	0.1291	0.0469
	10 – 30 Hz	0.0445	0.0618	0.1948

Table 2: RMS value of transmissibility magnitude.

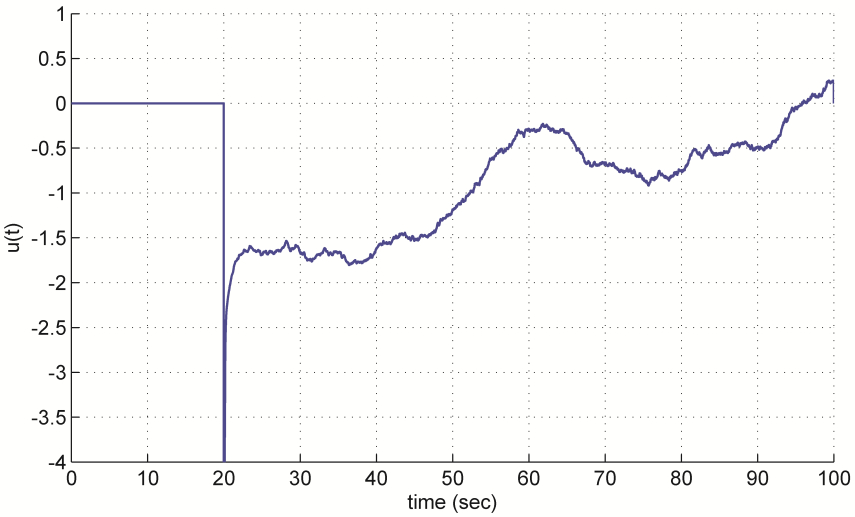

Figure 5: Normalized AFSMC-AFP control signal for seismic vibration VC-C ground vibration ($\tau = 0.01$s).

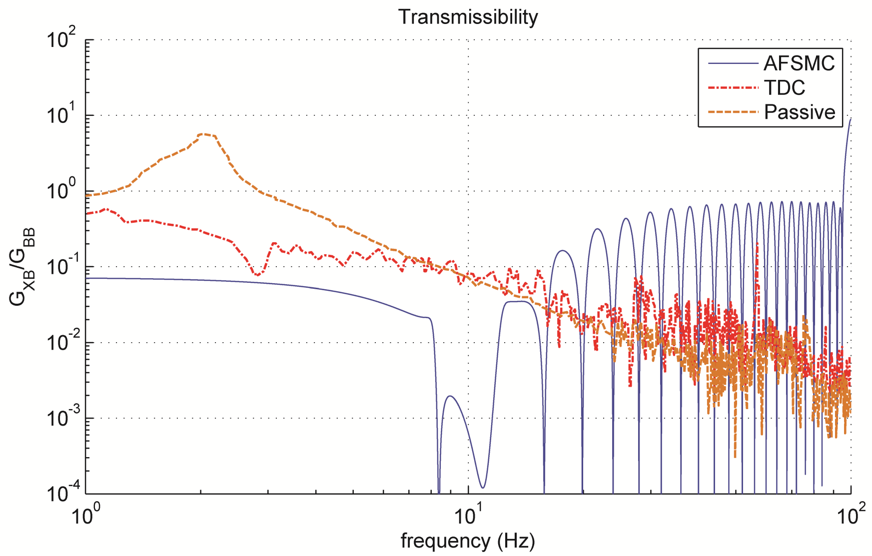

Figure 6: Transmissibility of passive, active, and AFSMC controlled pneumatic vibration table in presence of VC-C ground vibration ($\tau = 0.01$s).

5 CONCLUSION

In this paper, a new method of adaptive active control is proposed for the pneumatic vibration isolation tables. As the ground isolation requirements of vibration sensitive equipment become more stringent, the active control of such devices are unavoidable. In the previous sections it is shown that the proposed adaptive fuzzy sliding mode control with adaptive fuzzy predictor can handle this problem in a good way. This method does not require the precise model and magnitude of the uncertainties. Also, the linearity or nonlinearity of model is not important. AFSMC design results in the desired low-amplitude response, thus attaining a higher isolator performance.

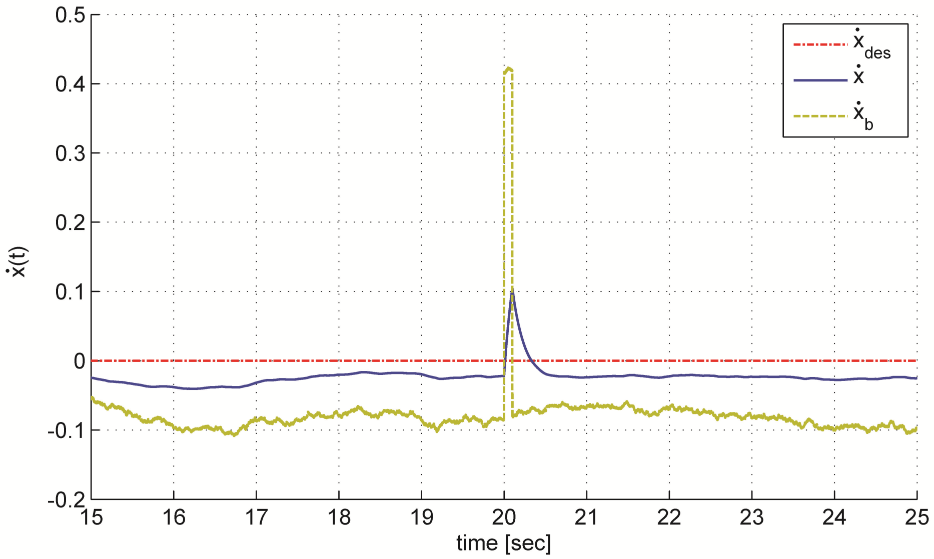

Figure 7: Normalized System velocity response to seismic vibration and direct disturbance at $t = 20$ s.

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