Adaptive feed-forward controller of piezoelectric actuator for micro/nano-positioning

S K SHOME^{1,*}, A MUKHERJEE¹, P KARMAKAR² and U DATTA¹

¹Academy of Scientific and Innovative Research (AcSIR), Central Mechanical Engineering Research Institute, Council of Scientific and Industrial Research Campus, Durgapur 713209, India

²Central Mechanical Engineering Research Institute, Council of Scientific and Industrial Research, Durgapur, India

e-mail: saikatkumarshome@gmail.com

MS received 26 May 2017; revised 16 March 2018; accepted 10 April 2018; published online 14 August 2018

Abstract. In this paper, design and implementation of an adaptive feed-forward controller for micro/nano-positioning control of piezoelectric actuator (PEA) is described. Discrete-time Dahl hysteresis-based mathematical model of the PEA is developed and the values of the model parameters are estimated through an autoregressive with exogenous terms (ARX) model identification technique using experimental input–output data. A recursive least-square estimator (RLSE)-based adaptive feed-forward (FF) controller is proposed, which takes into account the parameter uncertainty. The FF controller has also been implemented in a DsPIC30F4011 microcontroller. The established PEA model and the controller are validated by simulation and experimental results including parameter variation.

Keywords. Adaptive control; piezoelectric actuator; micro/nano-positioning; RLSE.

1. Introduction

With rapid development in engineering and technology, everything goes for miniaturization, which necessitates ultra-precise positioning systems in industrial applications. Quite a few system applications call for positioning accuracy down to nanometre resolution. Recently, the domain of precision positioning has been dominated by a class of actuators called piezoelectric actuators (PEAs) and have emanated to be the most favoured class of actuators in this field. The eminence of PEA can be attributed to some of its inherent advantages, e.g., large operating bandwidth, generate large mechanical force per unit mass with low power consumption, small thermal expansion during actuation, fast response and high resolution.

Typically, micro/nano-manipulation with dynamically interactive application needs actuators that can accurately perform reference tracking as well as yield robust force control. Nowadays, PEA has found widespread commercial applications in the field of optics, photonics, measuring technology, nano-metrology, micro-lithography, scanning microscopy, etc. [1–4]. Precision motion control using piezo-actuators has been reported to be a promising

approach and numerous research works have reported improving its efficiency in recent times [5–13]. Al-Wahab *et al* [14] have presented a methodology for the appropriate selection and creation of mechatronic handling devices, which can be capable of accomplishing certain micro- and/or nano-operation task using piezo-actuators.

Piezo-actuators also find considerable usage in high-precision dual-stage servo systems which has been reported in [15].

Though PEA is a promising actuator, these objectives are severely hampered due to some inherent nonlinearity like hysteresis, creep and vibration, the effects of which get more pronounced at smaller scales. However, they can be minimized with proper modelling and control. Out of these, the primary nonlinearity that adversely effects precision positioning is hysteresis. Hysteresis is also known for introducing limit cycles and chattering in addition to introducing severe positioning inaccuracies. Besides, the variation of system dynamics with environmental and loading condition also needs to be considered during control of a piezoelectric-material-actuated platform. Furthermore, the presence of creep in PEA causes a change in displacement with time without any accompanying change in the control voltage. This degrades the positioning accuracy of the system. This necessitates the requirement of a controller that can change its behaviour in response to the modification in dynamics of the processes and the disturbances acting on the system along with proper system

*For correspondence

modelling. Accordingly, an adaptive feed-forward (FF) control system can be utilized. The effects of hysteresis of piezo-actuators have been modelled and compensated by Viswamurthy and Ganguli [16] and Viswamurthy *et al* [17] to reduce trailing edge flap vibration in helicopters. Liaw and Shirinzadeh [18] have presented a robust adaptive constrained motion tracking control methodology for piezo-actuated flexure-based micro/nano-manipulation mechanisms. This unique control approach is established for the tracking of desired motion trajectories in a constrained environment exhibiting some degree of uncertainty in stiffness. In order to improve the high-resolution positioning performances of the microgripper, its actuators are modelled and a control law for both the position and the manipulation force is synthesized in [19]. In [20], a study of cascaded feedback and FF controller is presented to compensate hysteresis, creep and vibration effects of a piezo-scanner for high-speed positioning in AFM.

Constant gains in traditional feedback may increase the oscillations in the control signal and induce the excitation of high-frequency unmodelled dynamics of the system, which are undesirable phenomena [21]. To overcome this drawback, variable gains with adaptive rules have been reported in literature and found to be effective in the domain of piezo-actuation. Adaptive control is a dynamic and pivotal field of research in industrial applications. Over the past decade, importance of several self-adaptation-related application areas and technologies has increased [22–26]. It has also been applied in PEA systems by a number of researchers. In [27], an improved sliding mode control with PID-type sliding surface and adaptive gains is proposed for the motion tracking of PEA, where the controller requires only the online estimation of perturbation and control gains without acquiring the knowledge of bounds on system uncertainties. An adaptive proportional-integral (PI)-based sliding mode control design is proposed in [28] for nano-positioning of PEA, where the hysteresis and model imperfections are treated as uncertainties and addressed by sliding mode control. In [29], an adaptive approximator-based back-stepping control approach is proposed for trajectory tracking of the single-axis PEA-driven stages, which can provide an improvement in transient performance and tracking errors, and robustness to the load disturbance.

A new adaptive controller structure is introduced in [30], which is capable of achieving a linear parameterization and a linear error model in the presence of a hysteresis nonlinearity. A robust adaptive law is used to update the controller parameters and hysteresis inverse parameters, which ensures the global boundedness of the closed-loop signals for a wide class of hysteresis models. An adaptive sliding mode control method is proposed in [31] for eliminating hysteresis effect and achieving highly precise output displacement of PEAs. Paper [32] presents an adaptive model predictive control technique for reducing hysteresis in PEAs based on autoregressive

exogenous (ARX) model. It is inferred that an adaptive controller with adjustable specification and mechanism for adjusting parameters is preferred for piezo-actuation where the parameters can be modified to compensate for the shift in dynamics of the system and the disturbances acting on the plant.

The fulfilment of any control paradigm depends on the choice of a suitable mathematical modelling of the physical phenomenon. Quite a few framework models have been studied that represent system performance to an appropriate degree. These frameworks provide a generic intuition into the behaviour of PEA and also lay mathematical formulations for advanced control system design and realization. Various methods have been developed for modelling of the nonlinearities in PEA such as the Maxwell Slip Model, Preisach Model, Bouc–Wen Model and Dahl model [33–38]; however, the latter two are the most commonly used. In this research, plant dynamics have been captured using a second-order Dahl model, which has been cited to be better than the second-order Bouc–Wen model in depicting asymmetric hysteresis loops [38]; moreover, it has less number of parameters and it is easy to construct the inverse model. Though the Dahl model has been reported to be a promising approach, majority of works have been carried out on continuous-time base. Discrete-time Dahl hysteresis model is more preferable as control schemes are usually deployed for sampled data systems.

In this paper a new recursive least-square estimator (RLSE)-based adaptive discrete-time FF controller is developed and implemented on DsPIC30F4011 microcontroller platform. The dynamical model of PEA actuator is represented by a mass–spring–damper system with hysteresis force that is designed using a Dahl model [38] in continuous-time domain. The PEA model along with Dahl hysteresis model has been converted to discrete-time domain. The system parameters are estimated using the ARX model identification method with the help of several experimental input–output data. However, since the system parameters change with time, an uncertainty factor in the parameters has been incorporated in the system model. The values of the parameters are updated in each time step by RLSE-based adaptive FF control. The control algorithm is implemented on a DsPIC30F4011 microcontroller. The developed discrete-time PEA model has been validated by comparing the simulation and experimental results using the same sinusoidal signal of multiple amplitudes and frequencies. The adaptive FF controller is also validated with simulation and experimental results with different input signals. The rest of this paper is organized as follows. In section 2, the mathematical modelling of PEA in continuous- and discrete-time domain is described. Section 3 focuses on model identification. Section 4 describes the proposed RLSE-based adaptive FF controller that generates the control voltage. Results are given in section 5, and conclusions are drawn in section 6.

2. Mathematical model of PEA

2.1 Continuous-time PEA model

In continuous-time domain, the dynamic model of PEA can be expressed in the form of a mass–spring–damper system with hysteresis force. The same is modelled using the Dahl hysteresis model [38], by the equation

$$M\ddot{x} + D\dot{x} + Kx = Tu - F_h \quad (1)$$

where M is the mass of the system, D is damping co-efficient, K is stiffness, T is piezoelectric coefficient, u is input voltage and F_h is the hysteresis effect of the system in terms of force. The Dahl hysteresis model can be represented by the following equations:

$$\dot{V} = A_h V \dot{x} + B_h u_p \dot{x} \quad (2a)$$

$$F_h = C_h V \quad (2b)$$

where the variable x denotes the displacement, $V = [v_1 \ v_2]^T$ is an intermediate state vector for the second-order model, u_p is taken as constant and the matrices can be written as follows:

$$A_h = \begin{bmatrix} 0 & 1 \\ -a_2 & -\text{sign}(\dot{x})a_1 \end{bmatrix}, \quad B_h = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad \text{and} \quad (3)$$

$$C_h = [b_1 \ \text{sign}(\dot{x})b_0]$$

In Eq. (3), a_1 , a_2 , b_0 and b_1 are hysteresis parameters and can be found from the following equations:

$$a_1 = \frac{2}{T_d} \ln \frac{P_{n-1} - P_s}{P_n - P_s} \quad (4)$$

$$a_2 = \frac{4\pi^2}{T_d^2} + \frac{a_1^2}{4} \quad (5)$$

$$b_1 = G_{dc}a_2 \quad (6)$$

$$b_0 = S_0 \quad (7)$$

Figure 1. Open-loop time domain step response for a piezoelectric actuator.

where T_d is the time period of the damped oscillations of the system, which is equal to $(t_2 - t_1)$ from figure 1. P_n is the overshoot of the n^{th} peak and P_s is the steady-state response. G_{dc} represents the initial gain and S_0 is the initial slope of the response in FFT when the system is given a step signal.

2.2 Discrete-time PEA model

For a digital control system, discrete-time system is more suitable than continuous-time system. Hence, the continuous PEA model is converted to a discrete-time domain. The differential equations (1)–(3) are converted into difference equations.

If the sampling time is h , then at the k^{th} time instant

$$\dot{x}(t) = \frac{x(k+1) - x(k)}{h} \quad (8)$$

$$\ddot{x}(t) = \frac{\dot{x}(k+1) - \dot{x}(k)}{h} \quad (9)$$

Using (8), we get

$$\ddot{x}(t) = \frac{x(k) - 2x(k-1) + x(k-2)}{h^2}. \quad (10)$$

Now, replacing the value of $\dot{x}(t)$ and $\ddot{x}(t)$ in (1), the PEA discrete-time model can be given as

$$x(k) = Ax(k-1) + Bx(k-2) + Cu(k) + DF_h(k) \quad (11)$$

where $A = \frac{2M+D}{M^2+D^2+h^2}$, $B = -\frac{M}{M^2+D^2+h^2}$, $C = \frac{T}{M^2+D^2+h^2}$, $D = -\frac{1}{M^2+D^2+h^2}$.

Now, the Dahl hysteresis force in continuous time can be expressed in discrete-time domain by replacing

$$\dot{V}(t) = \frac{V(k+1) - V(k)}{h}, \quad V(k) = \begin{bmatrix} v_1(k) \\ v_2(k) \end{bmatrix} \quad \text{and} \quad \dot{x}(t) = \frac{x(k+1) - x(k)}{h}$$

in (2a), (2b) and (2b), we get

$$v_1(k) = v_1(k-1) + v_2(k)\{x(k) - x(k-1)\}, \quad (12a)$$

$$v_2(k) = \frac{v_2(k-1) + u_p\{x(k) - x(k-1)\} - a_2v_2(k)\{x(k) - x(k-1)\}}{1 + a_1\{x(k) - x(k-1)\}\text{sgn}\left\{\frac{x(k) - x(k-1)}{h}\right\}}, \quad (12b)$$

$$F_h(k) = v_1(k)b_1\text{sgn}\left\{\frac{x(k) - x(k-1)}{h}\right\}b_0v_2(k). \quad (13)$$

Taking Z-transform of (11), the model of the system in Z-domain is obtained as

$$X(Z) = \frac{Z^2\{CU(Z) + DF_h(Z)\}}{Z^2 - AZ - B}. \quad (14)$$

3. Model identification

The PEA model can be assumed to be a second-order discrete-time transfer function in cascade with the Dahl-based hysteresis model. The parameters of the transfer function (figure 2a) A – D are evaluated with the help of several experimental input–output data using it as a black box model. The regeneration model ARX is used to identify the values.

$$\begin{aligned} F(q^{-1})y(k) &= q^{-d}H(q^{-1})u(k) + \varepsilon(k) \\ F(q^{-1}) &= 1 + f_1q^{-1} + \dots + f_nq^{-na} \\ H(q^{-1}) &= h_0 + h_1q^{-1} + \dots + h_nq^{-nb} \end{aligned} \quad (15)$$

where q is the delay operator, y is the output vector, u is the input vector and ε is the error between model output and actual output. Using the ARX model, the regressing model can be defined as

$$y(k) = \varphi^T \theta + e(k). \quad (16)$$

Here, the vector

$$\begin{aligned} \varphi^T &= [-y(k-1), -y(k-2), \dots, -y(k-n), \\ &u(k-d), u(k-d-1), \dots, u(k-d-m)] \end{aligned}$$

and unknown parameters

$$\theta^T = [f_1, f_2, \dots, f_n, h_1, h_2, \dots, h_n].$$

The least-mean-square cost function is

$$J(\hat{\theta}) = \sum_{k=1}^N [y(k) - \varphi^T(k)\hat{\theta}]^2. \quad (17)$$

Figure 2. (a) Block diagram of piezoelectric actuator. (b) Discrete-time Dahl model.

The $\varphi^T(k)\hat{\theta}$ is the predicted output and $y(k)$ is the real output. The derivative $\frac{\partial J(\hat{\theta})}{\partial \hat{\theta}}$ is set to zero to minimize the cost function. Therefore

$$\begin{aligned} \frac{\partial J(\hat{\theta})}{\partial \hat{\theta}} &= -2 \sum_{k=1}^N \varphi(k) [y(k) - \varphi^T(k)\hat{\theta}] \\ &= 0 \\ &= > \sum_{k=1}^N \varphi(k)y(k) = \left[\sum_{k=1}^N \varphi(k)\varphi^T(k) \right] \hat{\theta}. \end{aligned}$$

Finally, the unknown parameters can be estimated as

$$\hat{\theta}_N = \left[\sum_{k=1}^N \varphi(k)\varphi^T(k) \right]^{-1} \sum_{k=1}^N \varphi(k)y(k). \quad (18)$$

The least-square estimate in matrix notation is

$$\hat{\theta}_N = [\Phi^T \Phi]^{-1} \Phi^T Y \quad (19)$$

where

$$\sum_{k=1}^N \varphi(k)\varphi^T(k) = [\varphi(1) \dots \varphi(N)] \begin{bmatrix} \varphi^T(1) \\ \vdots \\ \varphi^T(N) \end{bmatrix} = \Phi^T \Phi \quad (20)$$

and

$$\sum_{k=1}^N \varphi(k)y(k) = [\varphi(1) \dots \varphi(N)] \begin{bmatrix} y(1) \\ \vdots \\ y(N) \end{bmatrix} = \Phi^T Y. \quad (21)$$

Here, Φ is a full rank matrix; thus $\Phi^T \Phi$ is invertible and least squares estimate exists.

The initial values of the parameters A – D of (11) can be evaluated with the help of (18), where

$$\varphi^T = [x(k-1), x(k-2), u(k), F_h(k)]$$

and

$$\theta^T = [A, B, C, D].$$

Input voltage at different frequencies and amplitudes are given to the actual PEA (P-841.20) and outputs of the system are recorded. The same inputs are given to the simulation model to determine the validity of the PEA model.

4. RLSE-based adaptive FF controller

The FF controller is designed to generate required control voltage to travel the desired distance by the PEA. The FF control voltage can be generated with the help of the mathematical model of the PEA. The initial values of the

parameters (A – D) are estimated using the method as discussed earlier. Values of these parameters change with time; hence, uncertainty $\nabla A, \nabla B, \nabla C$ and ∇D is considered for the parameters A, B, C and D , respectively. The PEA model (11) considering the parameter uncertainty can be represented as

$$x(k) = (A + \nabla A)x(k-1) + (B + \nabla B)x(k-2) + (C + \nabla C)u(k) + (D + \nabla D)F_h(k). \quad (22)$$

The control voltage u_{FF} is expressed as follows:

$$u_{FF}(k) = A_1x(k) + B_1x(k-1) + C_1x(k-2) + D_1F_h(k). \quad (23)$$

From (22)

$$A_1 = \frac{1}{(C + \nabla C)}, B_1 = -\frac{(A + \nabla A)}{(C + \nabla C)},$$

$$C_1 = -\frac{(B + \nabla B)}{(C + \nabla C)}, D_1 = -\frac{(D + \nabla D)}{(C + \nabla C)}$$

The recursive-least-square-based method is adopted to estimate and update the unknown parameters A_1, B_1, C_1 and D_1 of the system in a dynamic manner. The RLS method is the extended type of least-mean-square algorithm and it imposes adaptability in the system.

Let us assume

$$P^{-1}(k) = \sum_{k=1}^N \varphi(k)\varphi^T(k), \quad (24)$$

$$B(k) = \sum_{k=1}^N \varphi(k)y(k). \quad (25)$$

Therefore (18) can be written as

$$\hat{\theta}_k = P(k)B(k) \quad (26)$$

where $P(k)$ and $B(k)$ can be written in time-dependent form as

$$P^{-1}(k) = P^{-1}(k-1) + \varphi(k)\varphi^T(k), \quad (27)$$

$$B(k) = B(k-1) + \varphi(k)y(k). \quad (28)$$

Replacing (28) in (26)

$$P^{-1}(k)\hat{\theta}_k = B(k-1) + \varphi(k)y(k), \quad (29)$$

$$P^{-1}(k)\hat{\theta}_k = P^{-1}(k-1)\hat{\theta}_{k-1} + \varphi(k)y(k).$$

As from (26), we can write $\hat{\theta}_{k-1} = P(k-1)B(k-1)$.

Therefore $B(k-1) = P^{-1}(k-1)\hat{\theta}_{k-1}$.

Replacing (27) in (29)

$$P^{-1}(k)\hat{\theta}_k = \{P^{-1}(k) - \varphi(k)\varphi^T(k)\}\hat{\theta}_{k-1} + \varphi(k)y(k),$$

$$\hat{\theta}_k = \hat{\theta}_{k-1} + P(k)\varphi(k)[y(k) - \varphi^T(k)\hat{\theta}(k-1)]. \quad (30)$$

The matrix inverse lemma $(A + BCD)^{-1} = A^{-1} - A^{-1}B(C^{-1} + DA^{-1}B)DA^{-1}$ is used to derive a recursive equation for $P(k)$ rather than $P^{-1}(k)$ as in (31). Utilizing this lemma, we get the following equations for update of unknown parameters:

$$P(k) = P(k-1) - \frac{P(k-1)\varphi(k)\varphi^T(k)P(k-1)}{1 + \varphi^T(k)P(k-1)\varphi(k)}, \quad (31)$$

$$\hat{\theta}_k = \hat{\theta}_{k-1} + \frac{P(k-1)\varphi(k)}{1 + \varphi^T(k)P(k-1)\varphi(k)}[y(k) - \varphi^T(k)\hat{\theta}(k-1)]. \quad (32)$$

The parameters A_1 – D_1 are updated at each time step using RLS algorithm [39–41] (31)–(32), where $\hat{\theta}_k^T = [A_1, B_1, C_1, D_1]$ and $\varphi^T(k) = [x(k), x(k-1), x(k-2), F_h(k)]$. The block diagram of the simulation model of RLS-based FF controller of the PEA is shown in figure 3.

5. Results and discussion

The model parameters (A – D) of the discrete-time PEA are evaluated through model identification with the help of several experimental data, i.e., input (voltage)–output (position) data of the PEA, P841.20. The specification of the actuator is given in table 1. The displacement of the PEA is measured by the attached Strain Gauge Sensor (SGS) with the actuator, which is displayed on the display module of E-501.00. The relation between the output voltage of the sensor and the position of the PEA is developed using several experimental data. A mathematical equation is developed from these data to find the position of the actuator from the SGS sensor voltage. The initial parameters of the discrete-time PEA are estimated by model identification using experimental input–output data as discussed in section 3; the hysteresis parameters are calculated by the method as described in section 2. The initial values of the parameters are given in table 2.

The output position plots of the actual PEA (P841.20) and the simulation model using the same input signals with

Figure 3. RLS-based FF controller.

different amplitudes and frequencies are shown in figures 4 and 5. The sinusoidal input voltages of amplitude 10 and 50 V with frequency 1 and 10 Hz are used as an input of the PEA shown in figures 4a, 4c, 5a and 5c, respectively. The output position of actual experimental data and the output from the simulation model using the same input signal are shown in figures 4b, 4d, 5b and 5d. The initial parameters are updated using (31) and (32). The RLSE-based adaptive FF controller is first simulated using

Table 1. Specifications of the piezo-actuator.

Open-loop travel, at 0–100 V	30 μm
Closed-loop travel	30 μm
Integrated feedback sensor	SGS
Resolution, closed-loop/open-loop	0.6/0.3 nm
Static large-signal stiffness	27 N/ μm
Electrical capacitance	3.0 μF
Push force capacity	1000 N
Length	50 mm

Table 2. Values of model parameters.

Parameter	Value
A	− 0.43423
B	− 0.40844
C	4.3873×10^{-2}
D	-4.5833×10^{-5}
a_1	122
a_2	1.1775×10^6
b_0	0
b_1	1.849×10^6

Figure 4. (a) 10 V, 1 Hz input voltage of PEA, (b) output position plot of experimental data and simulation model using 10 V, 1 Hz input voltage, (c) 50 V, 1 Hz input voltage of PEA and (d) output position plot of experimental data and simulation model using 50 V, 1 Hz input voltage.

MATLAB-SIMULINK. The block diagram is shown in figure 3. A variation of approximately $\pm 0.5\%$ in initial values of the parameters A – D is considered, i.e., the uncertainties are $\nabla A = \pm 0.005A$, $\nabla B = \pm 0.005B$, $\nabla C = \pm 0.005C$ and $\nabla D = \pm 0.005D$. The desired sinusoidal trajectory of 5 μm amplitude, 5 Hz frequency and position error with $\pm 0.5\%$ variation in initial values of the parameters A – D is shown in figure 6.

Performance of the controller in a noisy environment has been observed against varying noise variance (table 3). An

Figure 5. (a) 10 V, 10 Hz input voltage of PEA, (b) output position plot of experimental data and simulation model using 10 V, 10 Hz input voltage, (c) 50 V, 10 Hz input voltage of PEA and (d) output position plot of experimental data and simulation model using 50 V, 10 Hz input voltage.

Figure 6. (a) 5 μm , 5 Hz sinusoidal desired input position trajectory, (b) error between output and input position with +0.5% variation in initial values of model parameters, (c) 5 μm , 5 Hz sinusoidal desired input position trajectory and (d) error between output and input position with 0.5% variation in initial values of model parameters.

RMS error of 2.67×10^{-9} is observed to a sinusoidal input position of $10 \mu\text{m}$, 10 Hz in a noiseless situation. Normally distributed Gaussian noise has been used to model the noise in simulation. It has been observed that the proposed controller gives satisfactory performance till a noise variance of 10^{-18} .

The FF controller is implemented using the DsPIC30F4011 microcontroller. The controller generates the required control voltage for a given desired distance. The control voltage is amplified by an amplifier and applied to the PEA. The experimental set-up is shown in figures 7 and 8. The position error (desired distance – measured distance) is plotted in figure 9a for two different measured data sets. The simulation results of the position error with same desired distance with $\pm 0.1\%$ variation in initial values of the parameters are shown in figure 9b.

Table 3. System performance in noisy environment.

Gaussian noise variance	RMS error
10^{-25}	2.676×10^{-9}
10^{-20}	4.117×10^{-9}
10^{-18}	4.117×10^{-9}
10^{-16}	3.148×10^{-8}
10^{-15}	9.927×10^{-8}
10^{-12}	3.138×10^{-6}
10^{-10}	3.148×10^{-5}
10^{-09}	9.924×10^{-5}

Figure 7. Close-up view of the piezoelectric actuator from Physik Instrumente.

Figure 8. Experimental set-up of feed-forward controller of PEA.

Figure 9. (a) Experimental results of error for different desired distances travelled by PEA. (b) Simulation results of error for different desired distances travelled by PEA with $\pm 0.1\%$ variation in initial values of the parameters.

6. Conclusion

Achieving precise micro/nano-positioning using PEAs is an approach suitable in practical applications for nonlinear system identification, including hysteresis and its control. The identification topology has been based on discrete-time Dahl-based hysteresis modelling of the piezo-actuator with its parameters being identified by an ARX model, which has been validated both in simulation and experiments. A new RLSE technique has been used to control the positioning in FF mechanism and update plant parameters dynamically. The composite control scheme has been simulated in Matlab platform. An RMS error of 0.026% is obtained to an input sinusoidal tracking signal of $10 \mu\text{m}$, 10 Hz , which is quite useful for several practical applications where accurate positioning is needed like in the field of optics, photonics, measuring technology, nano-

metrology, micro-lithography, scanning microscopy, etc. Results show impressive performance of the controller against parametric uncertainties as well as in disturbance rejection in the presence of noisy environment. The proposed controller has also been implemented on a real PEA using DsPIC30F4011 microcontroller and experimental results demonstrate the efficacy of the controller.

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