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Controller Design and Actuator Dynamics Identification for a Hybrid Simulation Testing System

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Abstract

This paper describes the development of a feedforward controller and an actuator dynamics identification procedure for a hybrid simulation testing system. The feedforward control is integrated with a linear feedback control that has the function to compensate for tracking errors due to modelling uncertainty and unknown reaction force of the device under test. During hybrid simulations it is crucial the compensation of actuation system dynamics in order to avoid instability. The compensation can be provided identifying the system dynamics. To this aim, a nonlinear parameter estimator, based on the extended Kalman filter, has been developed. Experimental results are presented in order to highlight the performance of the proposed nonlinear estimator

Keywords: feedforward control, hybrid simulation, nonlinear dynamics, extended Kalman filter, nonlinear parameter estimation

INTRODUCTION

Hydraulic actuation systems exhibit significant nonlinear behaviour due to the pressure-flow rate relationship, the dead zone of the control valve [1] and frictions [2]; these nonlinearities make the mathematical model more complex and, at the same time, highly limit the performance achieved by the classical linear controller [3]. The traditional and widely used approach to the control of hydraulic systems is based on a linear model or on the local linearization of the nonlinear dynamics about the nominal operating point [4].

Suitable adaptive approaches are also employed when there is no knowledge of the parameter values [5] and when initial adaptation stages are acceptable.

In this paper a model-based control system, able to follow the desired displacement law, is presented and its robustness properties are checked. To this end, a fifth order nonlinear model (5^{th}OM) of the test rig is derived and its validation illustrated. The 5^{th}OM fully describes the isolator test rig in terms of typical dynamics, soft and hard nonlinearities and consequently is assumed as completely faithful to the plant. Successively a feedforward control based on the nonlinear inverse model of the system is obtained. The feedforward loop is designed to compensate for the nonlinearity of the electrohydraulic system, including the dead zone of the system and the nonlinear flow gain of the control valve.

The feedforward control is integrated with a feedback control in order to compensate for the tracking errors due to modelling uncertainty and unknown reaction force of the device under test,

The controlled actuation system is employed for hybrid simulations (HSs). This method, also known as substructure testing, consists in dividing a structural system into physical substructures that are experimentally tested and numerical substructures that contain the rest of the structure, which are numerically simulated [6], [7]. In these actuation systems, inevitable amplitude and phase errors exist between the actuator command displacement and the effective one. This phase error (which can also be viewed as a time delay) introduces additional energy into the system and the experiment could become unstable [8]. Consequently, suitable actuator dynamics compensation methods are generally adopted in HSs.

The performance of a compensation algorithm is strictly related to the knowledge of the actuation system dynamics that varies in accordance with several testing conditions. This result implies methods that can be useful to identify in real-time the actual actuation system dynamics. In this paper, a nonlinear parameter estimator, based on the Extended Kalm Filter (EKF), is proposed for the real-time identification of the system model parameters. The robustness of the EKF with respect measurement noise makes this method particularly suitable for HSs.

The paper is organized as follows: in Section II, the test rig is described; in Sections III and IV, the test rig modelling and the controller design are illustrated, respectively. The HS procedure, the EKF methodology and the proposed model parameter estimation are presented in Sections V, VI and VII, respectively; in Section VIII, the experimental validation of the nonlinear estimator is described.

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TEST RIG DESCRIPTION

The test rig (Fig. 1, 2) consists of a fixed base, a hydraulic actuator and a sliding table (1.8 m x 1.59 m).

The experimental setup used has been designed to perform static and dynamic tests on base isolation systems.

The table motion is constrained to a single horizontal axis by means of linear guides. The isolator under test is placed between the sliding table (A) and the vertical slide (B) (Fig. 1).

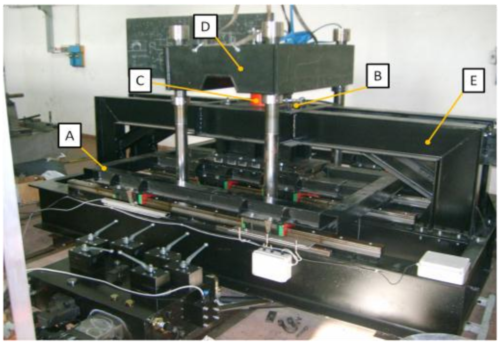


Figure 1: Test rig

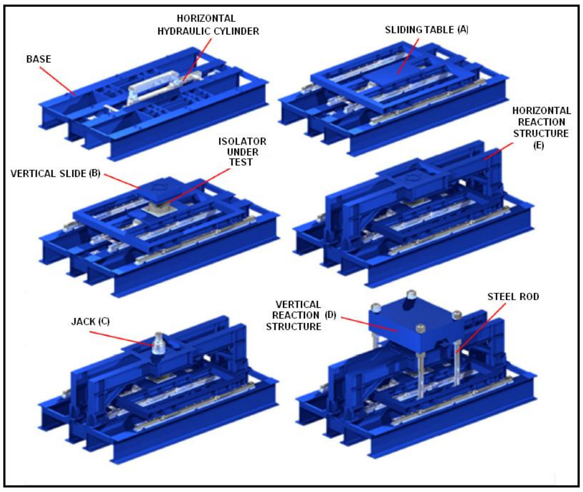


Figure 2: Test rig components

The hydraulic jack (C) allows the isolator under test (Fig. 2) to be vertically loaded (max 850 kN). The jack load and the force acting on the table are balanced by the vertical (D) and horizontal (E) reaction structures respectively.

The hydraulic circuit consists of a four way-three position proportional valve and a hydraulic cylinder. The cylinder is constituted by two equal parts separated by a diaphragm and contains two pistons whose rod is connected to the base: so, the actuator is characterized by a mobile barrel and fixed pistons [9]-[11]. The maximum horizontal force is 190 kN, the maximum speed is 2.2 m/s and the maximum stroke is 0.4 m (± 0.2 m).

The test rig is instrumented to detect the following measurements:

- table position y by means of magnetostrictive position sensor (FS = 0.4 m - estimated uncertainty = ± 1.2e-4 m);
- actuation force by means of strain gauge load cell (FS = 250000 N - estimated uncertainty = ± 500 N);
- pressure in the two chambers of the hydraulic cylinder (P_A and P_B in Fig. 3) by means of strain gauge sensor (FS = 400 bar - estimated uncertainty = ± 1 bar);
- supply pressure Ps by means of strain gauge sensor (FS = 400 bar - estimated uncertainty = ± 1 bar);
- valve spool position x_v by means of LVDT sensor integrated in the valve body;
- vertical load pressing on the specimen under test by means of strain gauge load cell (FS = 1e6 N - estimated uncertainty = ± 230 N).

The removal of the reaction structures allows the testing machine to be used as a shaking table and consequently as seismic simulator for test structures [12]-[14].

TEST RIG MODELLING

In the following section, the test rig mathematical model is derived. The modelling refers to the testing machine in which no isolator is installed: the hydraulic cylinder has to move only the sliding table (Fig. 3).

The modelling procedure is based on the following hypothesis: a) fluid properties not depending on the temperature; b) equal piston areas; c) equal oil volume for each side (with the barrel in a central position); d) negligible internal and external fluid leakages.

The test rig is modelled as a single DOF system subjected to both actuation and friction force. In particular, the actuator can be modelled as a double-ended hydraulic cylinder driven by a four-way spool valve.

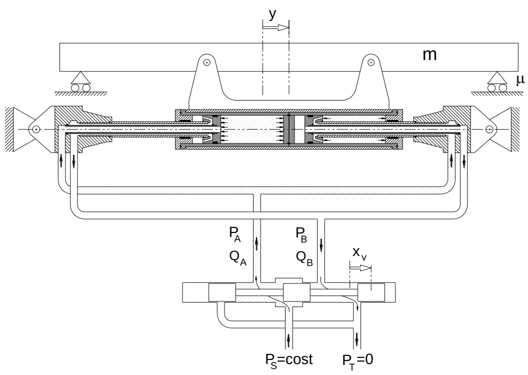


Figure 3: Scheme of the hydraulic actuator adopted for the mathematical model

In the following, the differential equations governing the hydraulic actuation system dynamics are given [15].

The pressure dynamics is given by:

$$\frac{V_0}{2\beta}\dot{P}_L = -A_p\dot{y} + Q_L \;, \qquad (1)$$

where $P_L = P_A$-P_B is the load pressure, P_A and P_B the pressures in the cylinder chambers, $V_0=V_A=V_B$ the oil volume between the piston and the valve in each side for the centered barrel position, A_p the piston area, $Q_L= (Q_A+Q_B)/2$, commonly called load flow, β the effective Bulk modulus and y the table displacement.

The motion equation of the sliding table is:

$$m\ddot{y} + \mu N \,\mathrm{sgn}(\dot{y}) + F_f = A_p P_L \,, \qquad (2)$$

where m is the movable mass, N the vertical load on the linear guides, μ the Coulombian friction coefficient and F_f the hydraulic friction force.

The hydraulic friction is modelled taking the viscous and the Coulombian term into account [16]-[19]:

$$F_f = \sigma\dot{y} + F_c\,\mathrm{sgn}(\dot{y}) \,, \qquad (3)$$

where σ is the viscous friction coefficient and F_c the Coulomb friction force. An overlapped four-way valve is considered: this kind of valve is typically characterized by the lands of the spool greater than the annular parts of the valve body. Consequently, the flow rate is zero (dead zone) when the spool is in the neighbourhood of its central position.

Under the assumption of a tank pressure P_T equal to zero, the load flow depends on the supply pressure, the load pressure and valve spool position in accordance with the following:

$$Q_L = DZ(v_e)\sqrt{P_s - \mathrm{sgn}(v_e)P_L} \;, \qquad (4)$$

where v_e is the voltage signal proportional to the valve spool position x_v and $DZ(v_e)$ is the dead zone function. More generically, neither the break-points nor the slopes of the dead zone are equal and, as consequence, the analytical expression of $DZ(v_e)$ is:

$$DZ(v_e) = \begin{cases} k_{qn}(v_e - v_{en}) & if \quad v_e < v_{en} \\ 0 & if \quad v_{en} \le v_e \le v_{ep} \\ k_{qp}(v_e - v_{ep}) & if \quad v_e > v_{ep} \end{cases} , \qquad (5)$$

where v_{en} and v_{ep} are the limits of the dead zone, k_{qn} and k_{qp} are the adopted gains if v_e is negative or positive respectively. The dead zone nonlinearity is among the key factors causing delay and error in the hydraulic actuation response.

As regards the valve dynamics, the following second order differential equation is adopted:

$$\frac{\ddot{v}_e}{\omega_{nv}^2} + \frac{2\xi_v}{\omega_{nv}}\dot{v}_e + v_e = v_c \;, \qquad (6)$$

where parameters ω_{nv} and ξ_v are the natural frequency and the damping ratio of the valve respectively and v_c is the valve command voltage due to its electronic driver. The relationship between v_c and the valve input voltage u is:

$$v_c = \begin{cases} k_{ep}u + v_{e0} & if \quad u > 0 \\ v_{e0} & if \quad u = 0 \\ k_{en}u + v_{e0} & if \quad u < 0 \end{cases} , \qquad (7)$$

where v_{e0} is the bias, and k_{ep}, k_{en} the gains. Finally, the equations governing the dynamics of the whole system (sliding table + hydraulic system) are:

$$\begin{cases} m\ddot{y} + (\mu N + F_c)\,\mathrm{sgn}(\dot{y}) + \sigma\dot{y} = A_p P_L \\ \dfrac{V_0}{2\beta}\dot{P}_L = -A_p\dot{y} + Q_L \\ Q_L = DZ(v_e)\sqrt{P_s - \mathrm{sgn}(v_e)P_L} \\ \ddot{v}_e = -\omega_{nv}^2 v_e - 2\xi_v\omega_{nv}\dot{v}_e + \omega_{nv}^2 v_c \end{cases} . \qquad (8)$$

The developed 5[th]OM fully describes the nonlinear dynamical behaviour of the hydraulic actuation system and takes the nonlinear friction forces and the nonlinear flow rate distribution into account.

CONTROLLER DESIGN

This section describes the development of the control system. The chosen controller scheme consists of a feedforward control, obtained by the validated 5[th]OM, integrated with a linear feedback controller with the function to compensate for tracking errors due to modelling uncertainty and unknown reaction force of the device under test. In this way, the feedback controller is not required to compensate for the large hydraulic proportional valve nonlinearities [20]-[23].

The feedforward process can be described as follows: denoting the nonlinear mapping G as the actual plant to be controlled, G is broken down into the known part, G_n (nominal), and the uncertain part, ΔG. That is, $G= G_n+\Delta G$. The term G_n represents a nonlinear mapping of all the known characteristics of the "plant" to be controlled. The term ΔG represents additive modelling uncertainty (e.g., the reaction force of the specimen under test) of G**.** Since the mapping G**,** is known, its inverse,G^{-1}, can be determined. Fig. 4 shows a control block diagram integrating the feedforward controller with the feedback control loop. The feedforward path uses the knowledge of the controlled plant, G_n, and the feedback path with loop gain factor K compensating for imperfections in the knowledge of the plant, ΔG.

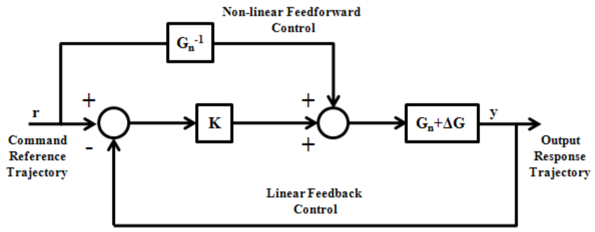


Figure 4: Control Block Diagram; Integrating Feedforward with Feedback control

If the parameter variation ΔG is zero, $\boldsymbol{y}$ perfectly follows r. When ΔG is non-zero, a higher achievable stable gain (K) reduces the effect of ΔG on the ability of y to track r (i.e., improves tracking performance). However, there are practical stability limits to the achievable gain.

HYBRID SIMULATION SYSTEM

In this section, the hybrid testing procedure is described. For HSs, the physical substructure interacts with a computational model (numerical substructure) by means of a feedback loop, exchanging information in real time with minimum error between them. The HS test set-up is shown in Fig. 5. The figure depicts a device, characterized by hysteretic nonlinearity [24], placed between the horizontal sliding table and the vertical actuator.

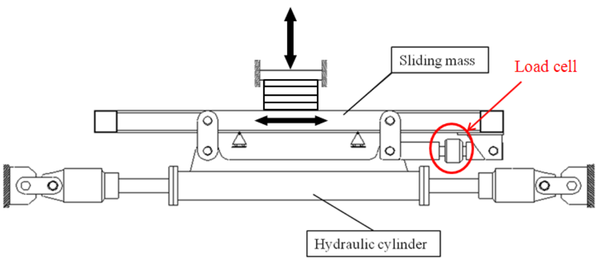


Figure 5: Scheme of the HS test set-up.

In HS of a base isolation system, a horizontal displacement is imposed on the bearing by means of the hydraulic actuator. Then, the measured reaction force is fed back to the numerical model for the solution of the equation of motion.

The adopted isolation device is commonly employed in seismic isolation [25]-[26], it consists of alternate layers of steel and elastomer connected by curing (Fig. 6).

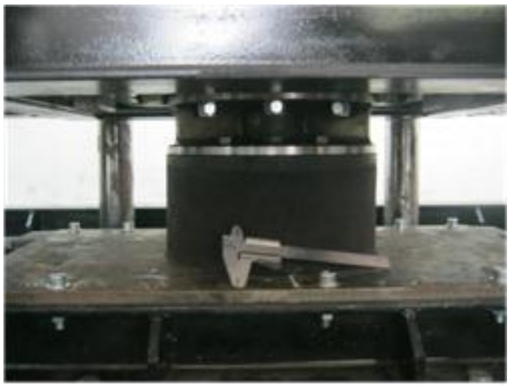


Figure 6: Seismic isolator.

EKF METHODOLOGY

The EKF is a mathematical tool for an optimal state estimation of nonlinear systems [27]. This algorithm can be used to estimate unknown parameters by taking the parameters as additional states and augmenting state equations [28]-[29].

The system and the measurement equations are:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) + \boldsymbol{\psi}(t)\,, \tag{9}$$

$$\mathbf{z}(t) = \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t)) + \mathbf{g}(t)\,, \tag{10}$$

being $\mathbf{x}$ the state vector, $\mathbf{u}$ the input vector, $\mathbf{f}$ a nonlinear function, $\boldsymbol{\psi}$ the process noise with covariance $\mathbf{Q}_k$, $\mathbf{z}$ the measurement vector, $\mathbf{h}$ a nonlinear function and $\mathbf{g}(t)$ the Gaussian white measurement noise with covariance $\mathbf{R}_k$.

The estimator has been implemented in a discrete time form with the state estimates and an estimation of the error covariance given by:

$$\hat{\mathbf{x}}_k^- = \mathbf{f}(\hat{\mathbf{x}}^+_{k-1}, \mathbf{u}_{k-1})\,, \tag{11}$$

$$\mathbf{P}_k^- = \mathbf{A}_{k-1}\mathbf{P}_{k-1}^+\mathbf{A}_{k-1}^T + \mathbf{L}_{k-1}\mathbf{Q}_{k-1}\mathbf{L}_{k-1}^T\,, \tag{12}$$

respectively.

In the previous formula the following parameters are defined

$$\mathbf{A}_{k-1} = \left.\frac{\partial \mathbf{f}}{\partial \hat{\mathbf{x}}}\right|_{\hat{\mathbf{x}}^+_{k-1}}\,, \tag{13}$$

$$\mathbf{L}_{k-1} = \left.\frac{\partial \mathbf{f}}{\partial \boldsymbol{\psi}}\right|_{\hat{\mathbf{x}}^+_{k-1}}\,. \tag{14}$$

The filter gain can be computed as in (15) to evaluate the measurement residual. The updates of state estimates can be computed as in (16), while the estimation of the error covariance can be determined as in (17):

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{M}_k \mathbf{R}_k \mathbf{M}_k^T)^{-1}, \qquad (15)$$

$$\hat{\mathbf{x}}^+{}_k = \hat{\mathbf{x}}^-{}_k + \mathbf{K}_k \left[\mathbf{z}_k - \mathbf{h}(\hat{\mathbf{x}}^-{}_k, \mathbf{u}_k)\right], \qquad (16)$$

$$\mathbf{P}_k^+ = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^-, \qquad (17)$$

where

$$\mathbf{H}_k = \left.\frac{\partial \mathbf{h}}{\partial \hat{\mathbf{x}}}\right|_{\hat{\mathbf{x}}^-{}_k}, \qquad (18)$$

$$\mathbf{M}_k = \left.\frac{\partial \mathbf{h}}{\partial \mathbf{g}}\right|_{\hat{\mathbf{x}}^-{}_k}. \qquad (19)$$

EKF-BASED CONTROLLED SYSTEM MODEL PARAMETER IDENTIFICATION

The dynamics of the controlled system depends on the actual plant (hydraulic actuation system, controller, specimen).

The dynamics of the controlled servo-system can be reasonably well approximated by a lower-order model with variable parameters that include the effects of the hydraulic actuation system, the controller and the specimen. The approximation can be considered accurate when high-frequency dynamics can be neglected (e.g., dynamics associated with oil-column resonance). The system transfer function can be written as:

$$G_{yr} = \frac{k_{yr}}{\tau_{yr} s + 1}, \qquad (20)$$

where τ_{yr} is a time constant and k_{yr} is an amplitude gain. The parameter values of Eq. (20) vary in function of the specimen and the actuator controller algorithm; moreover, the parameters change with respect to the amplitude of the reference signal because of inevitable nonlinearities.

The basic idea of this paper consists in using the EKF to identified the model parameters in real-time.

With reference to the case study, a suitable enlarged state vector has to be defined in order to estimate both the state variables and the desired parameters.

The differential equation associated to the transfer function (20) is

$$\tau_{yr} \dot{y} + y = k_{yr} r, \qquad (21)$$

that can be written in discrete time domain using the forward difference approximation:

$$y_k = \left(1 - \frac{\Delta t}{\tau_{yr}}\right) y_{k-1} + \left(\frac{k_{yr} \Delta t}{\tau_{yr}}\right) r_{k-1}, \qquad (22)$$

where Δt is a discretization time.

Considering the state vector

$$\mathbf{x}_k = \left[y_k \quad \tau_{yr,k} \quad k_{yr,k}\right] = \left[x_{1,k} \quad x_{2,k} \quad x_{3,k}\right], \qquad (23)$$

Eq. (22) can be formulated in the following state space form:

$$\begin{cases} x_{1,k} = \left(1 - \dfrac{\Delta t}{x_{2,k-1}}\right) x_{1,k-1} + \left(\dfrac{x_{3,k-1} \Delta t}{x_{2,k-1}}\right) r_{k-1} + w_{1,k-1} \\ x_{2,k} = x_{2,k-1} + w_{2,k-1} \\ x_{3,k} = x_{3,k-1} + w_{3,k-1} \end{cases} \qquad (24)$$

where w_1 is a Gaussian noise associated to the actuator displacement dynamics, w_2 and w_3 are fictitious Gaussian noise related to the unknown parameters.

In addition to Eq. (24), the measurement equation has to be introduced:

$$z_k = x_{1,k} + v_k \qquad (25)$$

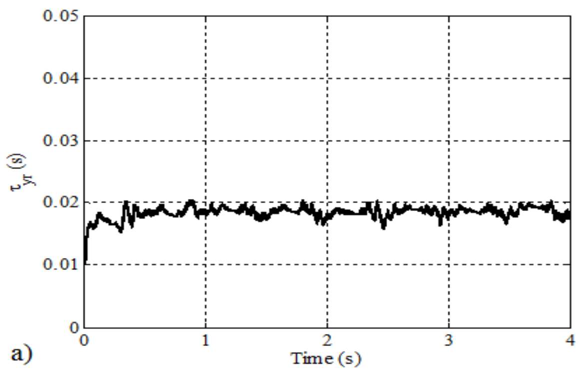
where v_k is the measurement noise.

EXPERIMENTAL RESULTS

The performances of the proposed estimator have been experimentally evaluated considering shear tests on the specimen shown in Fig. 6.

Considering the setup described in Section V, a sinusoidal target displacement characterized by a frequency f=1 Hz and an amplitude A=0.05 m has been imposed to the seismic isolator.

Fig. 7 shows the diagrams of estimated parameters.



a)

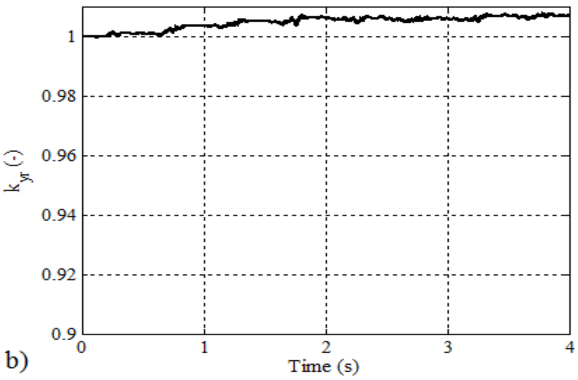


Figure 7: Experimental results: EKF-based parameter estimation; a) time constant diagram, b) amplitude gain diagram.

The diagrams of the estimated parameters, reported in Figs. 7a and 7b, show that the EKF converges to almost constant values for both parameters with a physical consistency concerning the actual servo-system dynamics.

CONCLUSION

An experimental/theoretical study has been carried out on the electrohydraulic actuation system of a hybrid simulation testing system. The plant consists of a hydraulically actuated unidirectional moving platform. A fifth order dynamic model of the system has been derived. The validated model has been considered for a position control design. The proposed approach consists in a feedforward control integrated with a feedback control. The feedforward control has been developed on the nonlinear inverse model of the system. The feedback controller has been adopted to compensate for the tracking errors due to modelling uncertainty and unknown reaction force of the device under test.

Successively, a nonlinear parameter estimator, based on the extended Kalman filter, has been proposed for the dynamics identification of the controlled test rig achieved for hybrid simulations of seismic isolators. The servo-system dynamics has been modelled with a first order model with parameters that vary in function of the actuation system configuration, the control algorithm and the specimen under test. Experimental results highlighted that the EKF-based estimator is able to reproduce the actual plant parameters in real-time.

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