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Experimental Comparison of New Adaptive PI Controllers Based on the Ultra-Local Model Parameter Identification

Hajer Thabet*, Mounir Ayadi, and Frédéric Rotella

Abstract: This paper is devoted to an experimental comparison between two different methods of ultra-local model control. The concept of the first proposed technique is based on the linear system resolution technique to estimate the ultra-local model parameters. The second proposed method is based on the linear adaptive observer which allows the joint estimation of state and unknown system parameters. The closed-loop control is implemented via an adaptive PID controller. In order to show the efficiency of these two control strategies, experimental validations are carried out on a two-tank system. The experimental results show the effectiveness and robustness of the proposed controllers.

Keywords: Adaptive PID controller, least squares method, linear adaptive observer, parameter estimation, robustness, trajectory tracking, two-tank system, ultra-local model control.

1. INTRODUCTION

Modern control system techniques are mostly based on an accurate mathematics modeling [1]. Therefore, describing the behavior of an industrial plant with simple and reliable differential equation is challenging due to the difficulties to adapt it at an industrial environment. Then, instead of relying on a complex accurate structure of the controlled system model, the ultra-local model control, which is an approach recently introduced by Fliess and Join [2–5], does not necessitate any mathematical modeling. The advantages of ultra-local model control and of the corresponding adaptive PID controllers led to a number of exciting applications in various fields [2, 4–6].

The used simple model is continuously updated with the aid of online estimation techniques [7–11]. The algebraic derivation method developed in [2] is restricted by the estimation of a single parameter, and the second parameter is considered constant and imposed by the practitioner. This paper presents fast identification methods allowing to estimate the two parameters of ultra-local model. The first technique is based on linear system resolution method which uses a simple calculus and linear algebra.

The second technique is based on the adaptive observer allowing the simultaneous estimation of state and unknown parameters. The design of adaptive observer ensures the joint state and parameter estimation, provided some persistent excitation conditions is satisfied. For multi-input-multi-output (MIMO) linear time varying

(LTV) systems, an adaptive observer, proposed in [12, 13], is conceptually simple and computationally efficient. For single-input-single-output (SISO) time invariant system, some results can be found in [14, 15]. Hence, the design of the proposed adaptive PID controller is based on an adaptive observer allowing the estimation of the two ultra-local model parameters.

An experimental and robustness comparison between the linear system resolution method and the adaptive observer based method is proposed in this paper. The aim is to estimate the ultra-local model parameters with two different methods. In order to clarify the performance obtained by these two techniques, the ultra-local model control is implemented for a two-tank water system. Therefore, this implementation is carried out to test the robustness performances with respect to the noises and disturbances rejection.

The paper is organized as follows: A short review of ultra-local model control and the corresponding adaptive PIDs controllers are presented in Section 2. Section 3 develops two different methods of online ultra-local model parameter identification: linear system resolution method and adaptive observer based method. An implementation of ultra-local model control on a two-tank system is studied in Section 4, where experimental results are shown. Some concluding remarks are provided in Section 5.

2. A SHORT REVIEW OF ULTRA-LOCAL MODEL CONTROL

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For simplicity's sake of the presentation, we assume that the system is SISO. The control input is denoted by u and the output is denoted by y . The input-output behavior of the system is assumed to be well approximated within its operating range by an ordinary differential equation:

$$E\left(y(t), \dot{y}(t), \dots, y^{(a)}(t), u(t), \dot{u}(t), \dots, u^{(b)}(t)\right) = 0, \quad (1)$$

which is nonlinear in general and unknown or at least poorly known. The ultra-local model control principle consists in replacing (1) by the ultra-local model:

$$y^{(\nu)}(t) = \hat{F}(t) + \hat{\alpha}(t)u(t), \quad (2)$$

where $\hat{F}(t)$ and $\hat{\alpha}(t)$ represent the model parameters containing all the structural information. Let us underline that these two parameters sum up the influence of disturbances and their derivatives.

As we have assumed that we do not know any model of the system, the order ν of the ultra-local model (2) can be arbitrarily chosen. In several existing examples, M. Fliess and C. Join indicate that ν may always be chosen quite, *i.e.*, 1 or 2, and 1 in all concrete situations.

2.1. Adaptive controllers design

Consider the ultra-local model (2), the desired behavior is obtained thanks to an adaptive controller as follows:

$$u(t) = \frac{-\hat{F}(t) + y^{(\nu)d}(t) + \Theta(e(t))}{\hat{\alpha}(t)}, \quad (3)$$

where:

- $y^d(t)$ is the output reference trajectory, obtained according to the precepts of the flatness-based control [16–18].
- $e(t) = y^d(t) - y(t)$ is the tracking error.
- $\Theta(e(t))$ is a causal, or non-anticipative, functional of $e(t)$, *i.e.*, $\Theta(e(t))$ depending on the past and the present, and not on the future (see [19] for more details about the functional).

The principle of ultra-local model based control is presented in the Fig. 1. This setting is too general and might not lead to easily implementable tools. This shortcoming is corrected in the following.

2.2. Adaptive PID controllers

Considering the case where $\nu = 2$, equation (2) becomes as follows:

$$\ddot{y}(t) = \hat{F}(t) + \hat{\alpha}(t)u(t). \quad (4)$$

Therefore, the loop is closed via an adaptive Proportional-Integral-Derivative controller [20, 21], or *a*-PID, given by

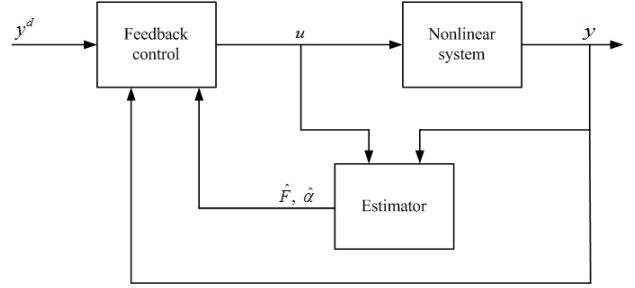


Fig. 1. Ultra-local model control.

the following control law:

$$u(t) = \frac{-\hat{F}(t) + \ddot{y}^d(t) + K_p e(t) + K_I \int e(t) + K_D \dot{e}(t)}{\hat{\alpha}(t)}. \quad (5)$$

Combining (4) and (5) yields to:

$$\ddot{e}(t) + K_D \dot{e}(t) + K_p e(t) + K_I \int e(t) = 0. \quad (6)$$

Note that the two functions $\hat{F}(t)$ and $\hat{\alpha}(t)$ don't appear anymore in the equation (6), *i.e.*, the unknown parts and disturbances of the system vanish. We are therefore left with a linear differential equation with constant coefficients of order 3. The tuning of K_p , K_I and K_D becomes therefore straightforward to obtain a good tracking of $y^d(t)$.

Assume now that $\nu = 1$ in (2):

$$\dot{y}(t) = \hat{F}(t) + \hat{\alpha}(t)u(t). \quad (7)$$

The desired behavior is achieved by the adaptive Proportional-Integral controller, or *a*-PI, defined by:

$$u(t) = \frac{-\hat{F}(t) + \dot{y}^d(t) + K_p e(t) + K_I \int e(t)}{\hat{\alpha}(t)}. \quad (8)$$

The combination of (7) and (8) gives:

$$\dot{e}(t) + K_p e(t) + K_I \int e(t) = 0. \quad (9)$$

The tracking condition is therefore easily satisfied by an appropriate choice of K_p and K_I . It boils down to the stability of a linear differential equation of order 2 with constant real coefficients.

3. ONLINE PARAMETER IDENTIFICATION METHODS

3.1. Algebraic derivation method of Fliess-Join

In the first publications on the ultra-local model control [2–4], a recent techniques based on the algebraic derivations of noisy signals [7, 8] are applied to estimate the parameter \hat{F} of the ultra-local model (2). However, the second parameter α of the model (2) is considered as constant

coefficient. For $v = 1$, the parameter $\hat{F}(t)$ is determined thanks to the knowledge of $u(t)$, α and the estimate of the first order derivative of output signal y which is written as follows:

$$\hat{y} = -\frac{3!}{T^3} \int_0^T (T-2t)y(t) dt, \quad (10)$$

where $[0, T]$ is quite short time window of estimation which is sliding in order to get the estimate \hat{y} at each time instant. At the sampling time kT_e (*i.e.* $t = kT_e$, where T_e denotes the sampling period), the estimate of \hat{F} is written as follows:

$$\hat{F}_k = \hat{y}_k - \alpha u_{k-1}, \quad (11)$$

where \hat{y}_k is the estimate of the first derivative of the system output that can be provided at the instant k , α is a constant design parameter, and u_{k-1} is the control input that has been applied to the system during the previous sampling time. In practice, the arbitrary choice of the static gain α present the first point that renders a delicate choice for the adaptive PID control strategy. However, the simultaneous estimation of the two parameters \hat{F} and $\hat{\alpha}$ by other alternative methods can provide a better improvement of results.

3.2. Linear system resolution method

Assuming the numerical control with constant sampling period T_e which allows to dispose on the system an available information until the instant kT_e and a constant control u_{k-1} between the two instants $(k-1)T_e$ and kT_e . From the simple model $\dot{y}(t) = \hat{F}(t) + \hat{\alpha}(t)u(t)$, the integration between two sampling instants gives:

$$\begin{aligned} y_k &= y_{k-1} + \int_{(k-1)T_e}^{kT_e} \hat{F}(t) dt + \int_{(k-1)T_e}^{kT_e} \hat{\alpha}(t)u(t) dt \\ &= y_{k-1} + \int_{(k-1)T_e}^{kT_e} \hat{F}(t) dt + \left[\int_{(k-1)T_e}^{kT_e} \hat{\alpha}(t) dt \right] u_{k-1}. \end{aligned} \quad (12)$$

Let \hat{F}_k and $\hat{\alpha}_k$ the mean values of $\hat{F}(t)$ and $\hat{\alpha}(t)$ in the interval $[(k-1)T_e, kT_e]$. Finally, we get:

$$y_k = y_{k-1} + \hat{F}_k T_e + \hat{\alpha}_k T_e u_{k-1}. \quad (13)$$

Considering the following notations:

$$Y_k = \frac{y_k - y_{k-1}}{T_e}, \quad H_k^T = \begin{bmatrix} 1 \\ u_{k-1} \end{bmatrix}, \quad \theta_k^T = \begin{bmatrix} \hat{F}_k & \hat{\alpha}_k \end{bmatrix}, \quad (14)$$

the previous equation (13) can be written in the following linear system form:

$$Y_k = H_k \theta_k. \quad (15)$$

Since the regression matrix $H_k = \begin{bmatrix} 1 & u_{k-1} \end{bmatrix}$ has a default rank. Then, this system is always consistent, *i.e.*, $\text{rank}[H_k] = \text{rank} \begin{bmatrix} H_k & Y_k \end{bmatrix}$. The aim is to seek at each instant kT_e the estimation of the parameter vector θ_k . According to the linear system resolution technique detailed in [22], the general expression of estimation is written as follows:

$$\theta_k = H_k^{\{1\}} Y_k + \left(I_{m+1} - H_k^{\{1\}} H_k \right) \Lambda_k, \quad (16)$$

where:

- $H_k^{\{1\}}$ denotes the Moore-Penrose generalized inverse of H_k , that is mean the matrix X such as $HXH = H$ [23],
- Λ_k is an arbitrary matrix of size $(m \times 1)$.

The coefficients of matrix Λ_k appear as degrees of freedom that can be used to satisfy other relating constraints to the system control, *e.g.*, optimization constraints. However, these degrees of freedom are equal to the rank of the matrix $I_{m+1} - H_k^{\{1\}} H_k$.

Based on the numerical knowledge of \hat{F} and $\hat{\alpha}$, the control input is calculated in (2) as a closed-loop tracking of a reference trajectory $t \rightarrow y^d(t)$, and a simple cancellation of the nonlinear terms \hat{F} and $\hat{\alpha}$.

3.3. Adaptive observer method

Before formally presenting the adaptive observer algorithm, we introduce some transformations on the structure of ultra-local model to properly formulate the problem. In the following, the two cases of ultra-local model, where $v = 1$ and $v = 2$, are studied. Firstly, consider the case where $v = 1$. Then, the ultra-local model (7) can be written in the following relation:

$$\begin{aligned} \dot{y}(t) &= \hat{F} + \hat{\alpha}u(t) \\ &= u(t) + \begin{bmatrix} 1 & u(t) \end{bmatrix} \begin{bmatrix} \hat{F} \\ \hat{\alpha} - 1 \end{bmatrix}. \end{aligned} \quad (17)$$

From the equation (17), the ultra-local model (7) can be represented in the form of a linear time-invariant SISO state-space system as follows (see the work of Q. Zhang [12] for more details about these systems):

$$\begin{aligned} \dot{x}(t) &= Bu(t) + \Psi(t)\theta, \\ y(t) &= Cx(t), \end{aligned} \quad (18)$$

where $x(t) \in \mathbb{R}$, $u(t) \in \mathbb{R}$ and $y(t) \in \mathbb{R}$ are respectively the state, input and output of the system, $\theta = \begin{bmatrix} \hat{F} & \hat{\alpha} - 1 \end{bmatrix}^T \in \mathbb{R}^p$ is a column vector of parameters assumed unknown, $\Psi(t) = \begin{bmatrix} 1 & u(t) \end{bmatrix} \in \mathbb{R}^{1 \times p}$ is a vector of measured signals. In this case, $A = 0$, $B = C = 1$ and $y(t) = x(t)$.

Now, consider the case where $v = 2$, and assuming the state vector $x(t) = [y(t) \quad \dot{y}(t)]^T$. The ultra-local model (4) is transformed in the following matrix form:

$$\begin{aligned} \dot{x}(t) &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ \hat{F} \end{bmatrix} + \begin{bmatrix} 0 \\ \hat{\alpha} \end{bmatrix} u(t) \\ &= \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} 0 & 0 \\ 1 & u(t) \end{bmatrix} \begin{bmatrix} \hat{F} \\ \hat{\alpha} - 1 \end{bmatrix}. \end{aligned} \quad (19)$$

From the relation (19), the following linear time-invariant SISO state-space system is obtained. This formalism allows us to apply the adaptive observer of Q. Zhang developed in [25]:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + \Psi(t)\theta, \\ y(t) &= Cx(t), \end{aligned} \quad (20)$$

where:

- The matrix A and the vectors B and C are defined by:

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C = [1 \quad 0].$$

- The matrix of measured signals $\Psi(t)$ and the vector of parameters are given as follows:

$$\Psi(t) = \begin{bmatrix} 0 & 0 \\ 1 & u(t) \end{bmatrix}, \quad \theta = \begin{bmatrix} \hat{F} \\ \hat{\alpha} - 1 \end{bmatrix}.$$

The design of an adaptive observer is studied in the following in order to estimate the state $x(t) \in \mathbb{R}^n$ and the parameters $\theta \in \mathbb{R}^p$ from the measured signals $u(t) \in \mathbb{R}$, $y(t) \in \mathbb{R}$, $\Psi(t) \in \mathbb{R}^{n \times p}$, and the matrices A, B, C . In practice, it is difficult to check the uniform complete observability [24] of the extended system (20) that should take into account some persistent excitation condition. Therefore, instead of assuming the uniform complete observability of the extended system, the adaptive observer developed in this paper is based on the stabilizability of the matrix pair (A, C) and on some persistent excitation conditions, described in the following assumptions Assumption 1 and Assumption 2. Noting that the assumptions proposed in [25] are designed for MIMO time-varying systems, however, the two following assumptions are restricted to SISO systems with constant matrices A, B and C .

Assumption 1: Assume that the matrix pair (A, C) in system (20) is such that there exists a vector of constant gain $K \in \mathbb{R}^n$ so that the system:

$$\dot{\eta}(t) = [A - KC]\eta(t) \quad (21)$$

is globally exponentially stable.

Assumption 2: Let $\Upsilon(t) \in \mathbb{R}^n \times \mathbb{R}^p$ be a matrix of signals generated by a stable filter such as:

$$\dot{\Upsilon}(t) = [A - KC]\Upsilon(t) + \Psi(t). \quad (22)$$

Assume that $\Psi(t)$ is persistently exciting so that there exist two positive constants δ and L such that, for all t , the following inequality is satisfied:

$$\int_t^{t+L} \Upsilon^T(\tau) C^T C \Upsilon(\tau) d\tau \geq \delta I \quad (23)$$

with $I \in \mathbb{R}^p \times \mathbb{R}^p$ the identity matrix.

Assumption 1 states that for any given parameter θ , a state observer with exponential convergence can be designed for system (20). The gain K sets the estimator dynamics. Assumption 2 is a persistent excitation condition, typically required for system identification.

Theorem 1: Let $\Gamma \in \mathbb{R}^p \times \mathbb{R}^p$ be any symmetric positive definite matrix. Therefore, under Assumptions 1 and 2, the following system of ordinary differential equations:

$$\begin{aligned} \dot{\hat{x}}(t) &= A\hat{x}(t) + Bu(t) + \Psi(t)\hat{\theta}(t) \\ &\quad + [K + \Upsilon(t)\Gamma\Upsilon^T(t)C^T][y(t) - C\hat{x}(t)], \end{aligned} \quad (24)$$

$$\dot{\hat{\theta}}(t) = \Gamma\Upsilon^T(t)C^T[y(t) - C\hat{x}(t)] \quad (25)$$

is a global exponential adaptive observer for the system (20).

Remark 1: The matrix $\Upsilon(t)$ is generated by a stable linear filtering of $\Psi(t)$ (for more details, see [12, 13]). Typically, the gain vector K is chosen only to ensure the stability of $(A - KC)$, the total gain for the state estimation being $K + \Upsilon(t)\Gamma\Upsilon^T(t)C^T$. Γ allows to set the rate of convergence between the state and the parameters.

Remark 2: For any initial conditions $x(t_0)$, $\hat{x}(t_0)$, $\hat{\theta}(t_0)$ and $\forall \theta \in \mathbb{R}^p$, the estimation error $\hat{x}(t) - x(t)$ tend to zero exponentially fast when $t \rightarrow \infty$.

The proof of theorem 1 requires the following lemma.

Lemma 1: Let $\phi(t) \in \mathbb{R} \times \mathbb{R}^p$ be a bounded and piecewise continuous matrix and $\Gamma \in \mathbb{R}^p \times \mathbb{R}^p$ be any symmetric positive definite matrix. If there exist positive constants L, δ such that $\forall t$:

$$\int_t^{t+L} \phi^T(\tau)\phi(\tau)d\tau \geq \delta I, \quad (26)$$

then the system:

$$\dot{z}(t) = -\Gamma\phi^T(t)\phi(t)z(t) \quad (27)$$

is exponentially stable.

The lemma of the case with a symmetric positive definite matrix Γ can be proved by simply adapting the proof of [26].

Proof of Theorem 1: For notational convenience, the variables are writing independently of t . The combination of the two adaptive observer equations (24) and (25) yields to:

$$\dot{\hat{x}} = A\hat{x} + Bu + \Psi\hat{\theta} + K(y - C\hat{x}) + \Upsilon\dot{\hat{\theta}}.$$

Let $\tilde{x} = \hat{x} - x$, $\tilde{\theta} = \hat{\theta} - \theta$ and notice that $\dot{\theta} = 0$, then:

$$\dot{\tilde{x}} = (A - KC)\tilde{x} + \Psi\tilde{\theta} + \Upsilon\tilde{\theta}. \quad (28)$$

The key step of the proof is to define the following linear combination of \tilde{x} and $\tilde{\theta}$:

$$\eta(t) = \tilde{x}(t) - \Upsilon(t)\tilde{\theta}(t).$$

After some simple computation, we obtain:

$$\dot{\eta} = (A - KC)\eta + [(A - KC)\Upsilon + \Psi - \dot{\Upsilon}]\tilde{\theta}.$$

Since Υ is generated by (22), we simply get:

$$\dot{\eta} = (A - KC)\eta. \quad (29)$$

By construction $(A - KC)$ is asymptotically stable, so $\eta \rightarrow 0$ with exponential convergence. Now we should study the behavior of $\tilde{\theta}$. As $\dot{\theta} = 0$, we have:

$$\begin{aligned} \dot{\tilde{\theta}} &= \Gamma\Upsilon^T C^T (y - C\hat{x}) = -\Gamma\Upsilon^T C^T C\tilde{x} \\ &= -\Gamma\Upsilon^T C^T C (\eta + \Upsilon\tilde{\theta}). \end{aligned} \quad (30)$$

Let us first look at the homogeneous part of system (30), that is:

$$\dot{\tilde{\theta}} = -\Gamma\Upsilon^T C^T C\Upsilon\tilde{\theta}. \quad (31)$$

Since Ψ is bounded, then Υ generated from the exponentially stable system (22) is also bounded. From the persistent excitation condition (23) and by applying Lemma 1 with $\phi = C\Upsilon$, (31) is exponentially stable. From the exponential convergences of η and of system (31), we prove that $\tilde{\theta} \rightarrow 0$ when $t \rightarrow \infty$. Finally, from $\eta \rightarrow 0$, $\tilde{\theta} \rightarrow 0$ and the fact that Υ is bounded, we conclude that $\tilde{x} = \eta + \Upsilon\tilde{\theta} \rightarrow 0$ with global exponential convergence. In the following, a practical implementation of the two proposed ultra-local model control approaches for a two tank system is given. In the both control techniques, the previous designed adaptive PI controller is considered.

4. TWO-TANK-SYSTEM APPLICATION

4.1. Nonlinear model system

The experimental system used is a two-tank-system described in Fig. 2. This system consists of a pump and two tanks with orifices and level sensor at the bottom of the upper tank. The pump provides infeed to the upper tank and the outflow of upper tank becomes infeed to the lower tank. In this system, the two identical water tanks have the same section S . Denote by $h_1(t)$ the water level in the upper tank, which also represents the system output and $h_2(t)$ the water level in the lower tank. The nonlinear model of the considered system is defined by the following representation:

$$\begin{aligned} \dot{h}_1(t) &= -\frac{k_1}{S}\sqrt{h_1(t)} + \frac{K}{S}V_p(t), \\ \dot{h}_2(t) &= \frac{k_1}{S}\sqrt{h_1(t)} - \frac{k_2}{S}\sqrt{h_2(t)}, \end{aligned} \quad (32)$$

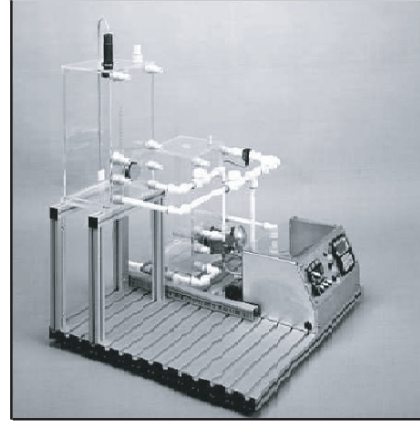


Fig. 2. Two-tank-system.



Fig. 3. The experimental setup of acquisition and control system.

where K is the pump constant and $V_p(t)$ is the voltage applied to the pump. The term $k_i\sqrt{h_i(t)}$, $i = 1, 2$, comes from the gravity flow. The two parameters k_1 and k_2 represent the coefficients of the canalization restriction. These two equations are nonlinear due to the presence of the term $\sqrt{h(t)}$, hence the most difficult task in the control of this considered system will be the control of the water level $h_1(t)$ in different operating conditions.

4.2. Control design

For implementing the proposed ultra-local model control, we choose to generate a desired trajectory $h_1^d(t)$ ensures a transition from $h_1^d(t_0) = 2$ V to $h_1^d(t_f) = 3$ V with $t_0 = 100$ s and $t_f = 300$ s. Fig. 3 displays a full description of our acquisition and control system. The pump ensures the filling of the upper tank and it is controlled by a PC which serves as a real-time target to Simulink. The filtered measurements are acquired by the acquisition card PCI-1711. This card provides the communication between the two-tank system and the PC during the running in automatic mode. The measurements are filtered by a first order with time constant T . The system parameters are summarized in Table 1.

For the experimental applications of control approaches, the same a -PI controllers are implemented

Table 1. Parameter values of the considered system.

Parameter	Value
S	332.5 cm^2
k_1	$42.1 \text{ cm}^{5/2}/\text{s}$
k_2	$42.1 \text{ cm}^{5/2}/\text{s}$
K	16.65

with $K_P = 20$ and $K_I = 3.5$. In the case of linear system resolution (LSR) method, we choose $T_e = 0.1 \text{ s}$ and $\Lambda_k = [-2.5 \ 0.5]^T$. The parameters of the adaptive observer (AO) based method in the case of $\nu = 1$, are chosen $K = 10$ and $\Gamma = \text{diag}([5, 0.05])$.

4.3. Experimental results

Figs. 4 and 5 present the experimental results of the proposed control approaches. For the experiments, the measurements of the level water in the upper tank are filtered by a low pass filter with time constant $T = 0.3 \text{ s}$. This filter is added in order to attenuate the influence of the quick fluctuations. At $t = 325 \text{ s}$, a level water perturbation which simulates a default sensor, is applied directly to the system in order to test the robustness of our proposed control approaches. Noting that the same response time is obtained in the different experimental case-studies. This amounts to the choice of the same adaptive controller gains. It is clear that, the water level tracking performance is provided thanks to the proposed adaptive controllers. The ultra-local model control based on adaptive observer, when $\nu = 1$, provides better trajectory tracking performances (see Fig. 5) than the case of linear system resolution (LSR) method. Moreover, the water level perturbation is quickly and similarly rejected in the different cases of a -PI controllers. In the two figures 4, 5, we can observe the smoothness of the control inputs which have practically the same magnitudes.

Consequently, the good tracking performances and the good robustness towards the level water disturbances are obtained thanks to the proposed adaptive controllers which are based on an online estimation of the two ultra-local model parameters. Noting that the main aim of this paper is not the parameter identification but to obtain in each instant t parameters which satisfies the ultra-local model.

5. CONCLUSIONS

The main contributions of this paper are the design and the application of new ultra-local model control approaches for the water level system. The paper exposes an ultra-local model control with different proposed methods of parameter estimation. The experimental results show that the a -PI controllers approaches are able to ensure good trajectory tracking even in various operating condi-

tions. In addition, the ultra-local model controllers are robust with respect to corrupting noises and external disturbances. The most important benefit of this work is the online estimation of the two ultra-local model parameters which provide an improvement in terms of robustness performances.

Despite that the proposed control algorithms are innovative in the field of level water control, good performances in terms of robustness and tracking are obtained. Due to its robustness and simplicity of implementation, the ultra-local model control appears particularly adapted to industrial environments. Finally, it is straightforward to extend the ultra-local model control approaches to some MIMO systems.

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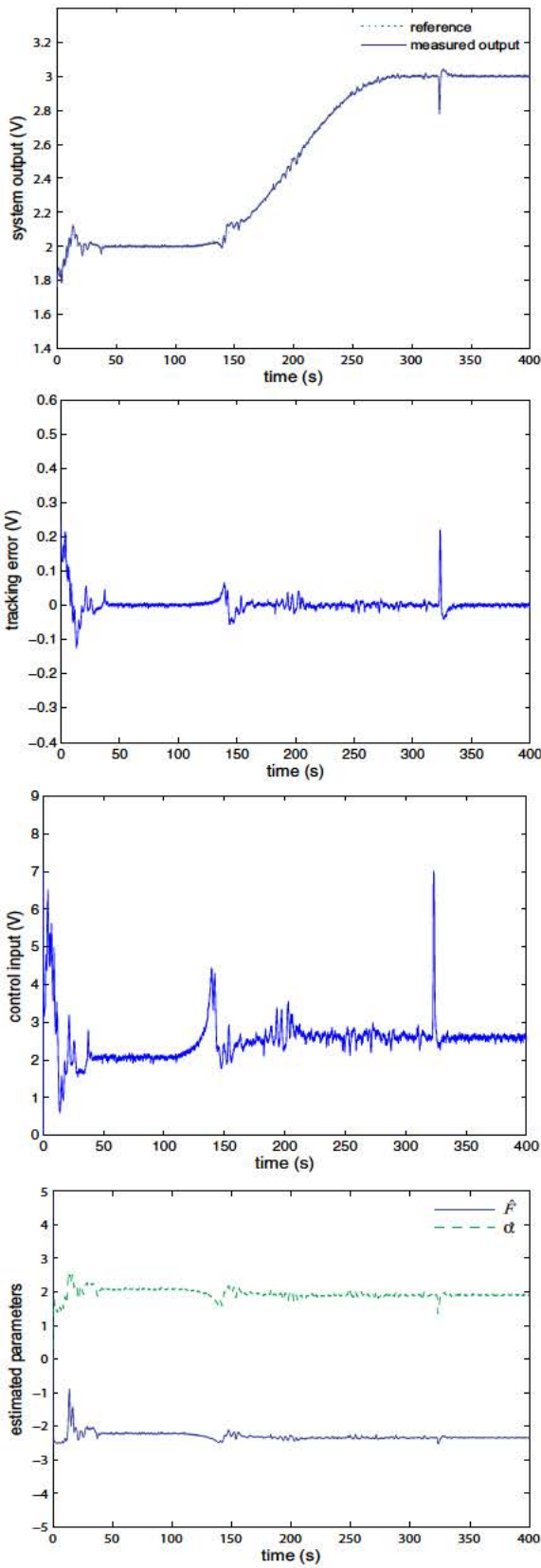


Fig. 4. Experimental results in the case of linear system resolution method.

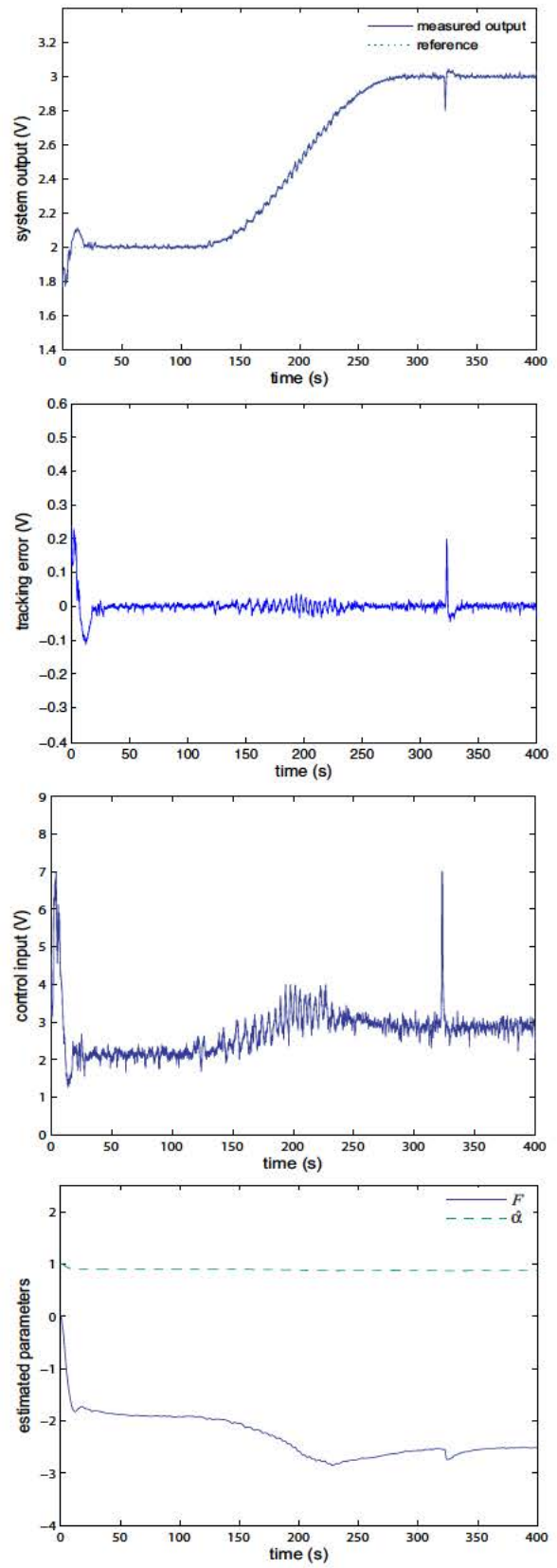


Fig. 5. Experimental results in the case of adaptive observer based method ($\nu = 1$).

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