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Derivative Based Control For LPV System With Unknown Parameters: An Application on a Permanent Magnet Synchronous Motors

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Abstract—This paper deals with the robust stabilization of a class of Linear Parameter Varying (LPV) systems in the continuous time case. Instead of using a state observer or searching for a dynamic output feedback, the controller is based on output derivative estimation. This allows the stabilization of the plant with very large parameter variation and uncertainties. The proof of stability is based on the polytopic representation of the closed loop, Lyapunov conditions and system transformations. The result is a control structure with only few parameters which are tuned via very simple conditions. This paper illustrates the usefulness on real application: Permanent Magnet Synchronous Motors (PMSM) position control.

Index Terms—Linear Time Varying systems, Robust control, Uncertainties, Linear Matrix Inequalities, Polytopic systems, Permanent Magnet Synchronous Motors.

I. Introduction

In the industrial process control field, the most common controllers are traditional PID which were developed in 1940s. These controller are very famous because of their low number of tuning parameters allowing in some cases empiric tuning. Unfortunately, due to their linear nature, the performance guarantee are often limited to a state-space region around a given set-point. For complex plants, it is really hard/impossible to tune them correctly without a good model or a more complex control structure. This is due to the nonlinear nature of most systems and the variation of their parameters.

Because internal states of most industrial plants cannot be directly measured and only their outputs are available for control purposes, output feedback controllers were considered. In output feedback design, static output feedback [1], [2], dynamic output feedback [3] and fuzzy observer-based control approaches [4], [5] have been employed. The design procedure of these controller need a good model and for some of them the use of complex optimization techniques. Even if the available model is good enough, using a dynamic model for computing the control law implies the identification of the model parameters. Unfortunately, the choice of the physical model structure, the identification of the model parameters, the experimental validation of model are never simple and are time consuming. Therefore, PID controllers are often tuned with a simple (linear) non physical model ([6], [7]). However, this could lead to poor results when a process has a large operating domain.

Two important aspects have to be considered in the output feedback control problem. The first one is related to the design of the feedback control law for any system such that the closed loop is stable and guaranteed performances and tracking. This problem has attracted much research effort which resolve this problem by considering for example the $\mathcal{L}_2$ gain, H_∞ norms (see [8], [9], [10]), robust LQ control [11], [12], [13]. The second one is related to the non availability of all variable parameters in real-time for implementation of complex control laws. As a matter of fact, the control law depends on the output of the system and on some of the varying parameters. If no information about these variable parameters is available, a constant (i.e., independent of the premise variables) output feedback control gain may be an alternative but yielding, in general, conservative results.

A solution to this problem is proposed based on some new results in the framework of *model free control* given by Cedric et al. [14]. The latter is signal based and don't require many information about the system. To implement this controller, the output derivatives has to be available in real time. In the literature, many variant of such controller have been developed (see [15], [16], [14], [17]). All these

studies state that the stability as well as performances are ensured but none of them provides a standard proof on a class of system.

There exist in the literature many techniques for the signal derivation. The simplest one is to use a linear derivative filter i.e. any stable transfer function with a stable denominator and a pure differentiators for the numerator. Other possibilities consist in the use of algebraic differentiators [18], [14], Luenberger unknown input observer or sliding mode observers [19], [20], [21], [22].

In this paper, a controller introduced by the authors in previous work [23] is considered. This controller is based on a signal differentiators and dynamic nullification. It has a fixed structure and only one parameter. In order to show the efficiency of this controller, a study case of PMSM (Permanent Magnet Synchronous Motors) position control is given. The stability of the system closed loop under parametric uncertainties is studied using the Lyapunov theory and polytopic transformation. The result is presented as a set of LMI (Linear Matrix Inequalities) to solve.

The first part of this paper describes the class of systems and the controller structure. The second is devoted to the description of the Permanent Magnet Synchronous Motors as well as its polytopic representation. The third part provides numerical LMI solutions ensuring the stability of the controlled PMSM under time varying parametric uncertainties. Some real experiments illustrates the consistency of this approach. The last part gives some conclusions and perspectives.

II. Problem formulation

A. The class of system

In this paper, we consider the following class of single input single output linear system with time varying parameters:

$$y^{(n)}(t) = -a_0(t)y(t) - \ldots - a_{n-1}(t)y^{(n-1)}(t) + \alpha u(t). \quad (1)$$

where $y(t) \in \mathbb{R}$ is the output, $u(t) \in \mathbb{R}$ is the control input and a_i are scalar time varying parameters.

For design simplification purposes, the system will be viewed as the following equation from the controller point of view:

$$y^{(v)}(t) = f(t) + \hat{\alpha}u(t). \quad (2)$$

It means that only the differential equation order v and an approximation of the parameter α are known. These two parameter are the easiest to get for most real system. In the formulation of the system equation given in (2), $f(t)$ is the function which contains all the dynamic information, i.e. the global dynamic of the system and the possible disturbances. The function $f(t)$ is assumed to be control independent.

***Remark** 1:* v is not necessarily equal to the model order n especially if the model has some fast stable dynamics.

B. The controller

Since the only information on the system are given by Equation (2), the idea of the controller structure is to nullify the system dynamic $f(t)$ and then replace it with the ideal dynamic for the closed loop. Considering this idea, we get the following controller (Fig. 1):

$$u(t) = -\frac{1}{\hat{\alpha}}(\hat{f}(t) + K\hat{Y}(t) - k_0 r(t)). \quad (3)$$

where $\hat{f}(t)$ is the estimate of $f(t)$, $\hat{\alpha}$ is an approximation of α, $r(t)$ is the reference, $\hat{Y}(t) = [z_0(t) \quad \ldots \quad z_{v-1}(t)]^T$ is a vector composed with $z_i(t)$ the estimation of $y^{(i)}(t)$ and $K = [k_0 \quad \ldots \quad k_{v-1}]$ is a vector with the coefficients of the ideal closed loop dynamic given by the specifications.
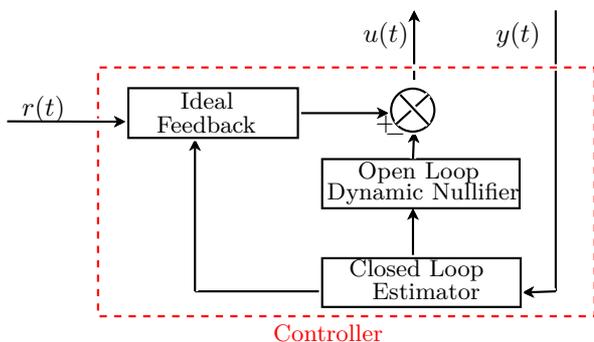

Fig. 1. Controller plant

C. Derivative estimation

In this part, the problem of estimation of $f(t)$ and the successive derivatives of $y(t)$ are considered. In order to get a simple solution, we consider linear filters for the output derivation:

$$\begin{cases} \frac{z_0(s)}{y(s)} = \frac{1}{\tau s + 1} \\ \frac{z_i(s)}{y(s)} = E(s)^i = \left(\frac{s}{\tau s + 1}\right)^{i+1} \quad \forall i = 1 \ldots v \end{cases} \quad (4)$$

This estimator is causal and ensures a good estimation if τ is sufficiently smaller than the fastest relevant dynamic of the system. It provides the successive estimations $z_i(t)$ of $y^{(i)}$.

***Remark** 2:* In the literature, many approaches were proposed: one can consider sliding mode estimation [19], [20], [21], [22], Luenberger observer based estimation and algebraic estimation [18].

The estimation of $f(t)$ is made by inverting the dynamic Equation (2) but instead of using the value of $u(t)$, a filtered version of it must be used. This is one of the possible solution to avoid the algebraic loop between $u(t)$ and $\hat{f}(t)$.

$$\hat{f}(t) = z_v(t) - \hat{\alpha}\hat{u}(t) \quad (5)$$

with $z_v(t)$ being the estimation of $y^{(v)}(t)$ and

$$\frac{\hat{u}(s)}{u(s)} = \frac{1}{\tau s + 1}.$$

III. Main result

Let consider the following model of Permanent Magnet Synchronous Motors (PMSM) in the rotation frame $(d-q)$ [24]:

$$\begin{cases} L\frac{di_d}{dt} & = & v_d - Ri_d + n_p Lwi_q \\ L\frac{di_q}{dt} & = & v_q - n_p Lwi_d - Ri_q - K_c w \\ J\frac{dw}{dt} & = & K_c i_q - f_v w \\ \frac{d\theta}{dt} & = & w \end{cases} \quad (6)$$

where v_q and v_d are the voltages applied to the two phases of the PMSM, i_d and i_q are the two phase currents, L is the inductance of a phase winding, R is the resistance of a phase winding, K_c is the back-EMF constant (and also the torque constant), w is the angular velocity of the rotor, θ is the angular position of the rotor, n_p is the number of pole pairs (or rotor teeth), J is the moment of inertia of the rotor (including the load) and f_v is the coefficient of viscous friction.

A. Closed loop State space representation

The state space representation of the different dynamic equation of the last section are given here. The model in the state space form is given by choosing the state vector as $x_m(t) = [i_d(t) \ i_q(t) \ w(t) \ \theta(t)]^T$, $v_d = 0$ and v_q as the system control input and the rotor angular position $\theta(t)$ as output:

$$\begin{cases} \dot{x}_m(t) & = & A_m(w(t))x_m(t) + B_m v_q(t) \\ y(t) & = & C_m x_m(t) \end{cases} \quad (7)$$

where

$$A_m(w(t)) = \begin{pmatrix} -R/L & n_p w(t) & 0 & 0 \\ -n_p w(t) & -R/L & -K/L & 0 \\ 0 & K/J & -f_v/J & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix},$$

$B_m^T = \begin{pmatrix} 0 & 1/L & 0 & 0 \end{pmatrix}$ and $C_m = \begin{pmatrix} 0 & 0 & 0 & 1 \end{pmatrix}$

Since the currents dynamics i_d and i_q are fast and stable, it is sufficient to consider a second order controller design $(v = 2)$. The controller (2) is based on the following model:

$$\begin{array}{rcl} y^{(2)}(t) & = & f(t) + \hat{\alpha} u(t) \\ \hat{\alpha} & = & \hat{K}/(\hat{J}\hat{R}) \end{array} \quad (8)$$

The reduced order controller can be represented as it follows where $\dot{x}_e(t) = [z_1(t) \quad z_2(t) \quad \hat{u}(t)]^T$:

$$\begin{cases} \dot{x}_e(t) & = & A_e x_e(t) + B_{ey} y(t) + B_{eu} v_q(t) \\ \hat{Y}(t) & = & C_{eyx} x_e(t) + C_{eyy} y(t) \\ \hat{u}(t) & = & C_{eu} x_e(t) \end{cases} \quad (9)$$

where:

$$A_e = \begin{pmatrix} -\frac{1}{\tau} & 0 & 0 \\ -\frac{1}{\tau^2} & -\frac{1}{\tau} & 0 \\ 0 & 0 & -\frac{1}{\tau} \end{pmatrix}, \ B_{eu}^T = \begin{pmatrix} 0 & 0 & \frac{1}{\tau} \end{pmatrix},$$

$$C_{eyx} = \begin{pmatrix} 1 & 0 & 0 \\ -\frac{1}{\tau} & 0 & 0 \end{pmatrix}, \ C_{eyy}^T = \begin{pmatrix} 0 & \frac{1}{\tau} \end{pmatrix},$$

$B_{ey}^T = \begin{pmatrix} \frac{1}{\tau} & \frac{1}{\tau^2} & 0 \end{pmatrix}$ and $C_{eu} = \begin{pmatrix} 0 & 0 & 1 \end{pmatrix}$.

Then, the estimation of the dynamic $f(t)$ is:

$$\hat{f}(t) = C_{fx} x_e(t) + C_{fy} y(t),$$

where:

$$C_{fx} = \begin{pmatrix} -\frac{1}{\tau^2} & -\frac{1}{\tau} & -\hat{\alpha} \end{pmatrix} \text{ and } C_{fy} = \frac{1}{\tau^2}.$$

By injecting the expression of (3) in (9), the controller can be represented as follows:

$$\begin{cases} \dot{x}_e(t) = A_o x_e(t) + B_{o_1} y(t) + B_{o_2} r(t) \\ v_q(t) = C_o x_e(t) + D_{o_1} y(t) + D_{o_2} r(t) \end{cases} \quad (10)$$

where

$$\begin{array}{rcl} A_o & = & A_e - \frac{B_{eu}}{\hat{\alpha}}(C_{fx} + KC_{eyx}) \\ B_{o_1} & = & B_{ey} - \frac{B_{eu}}{\hat{\alpha}}(C_{fy} + KC_{eyy}) \\ B_{o_2} & = & \frac{B_{eu}}{\hat{\alpha}} k_0 \\ C_o & = & -\frac{1}{\hat{\alpha}}(C_{fx} + K\ C_{eyx}) \\ D_{o_1} & = & -\frac{1}{\hat{\alpha}}(C_{fy} + K\ C_{eyy}) \\ D_{o_2} & = & \frac{k_0}{\hat{\alpha}} \end{array}$$

Finally the closed loop of the system (7) and its controller (10) is:

$$\begin{cases} \dot{x}(t) & = & A(w(t))x(t) + Br(t) \\ y(t) & = & Cx(t) \end{cases} \quad (11)$$

with the closed system state $x(t) = [x_m(t) \ x_e(t)]^T$,

$$A(w(t)) = \begin{pmatrix} A_m(w(t)) + B_m D_{o_1} C_m & B_m C_o \\ B_{o_1} C_m & A_o \end{pmatrix},$$

$$B = \begin{pmatrix} B_m D_{o_2} \\ B_{o_2} \end{pmatrix} \text{ and } C = \begin{pmatrix} 0_{(1 \times 3)} & 1 & 0_{(1 \times 3)} \end{pmatrix}.$$

Consider that $w(t)$ ranges between known extremal value $w(t) \in [\underline{w}, \ \overline{w}]$.

In this frame, the PMSM can be described using a LPV state space representation which depends on a time varying parameter $w(t)$.

B. Polytopic representation and stability analysis

There exist several ways to get stability conditions. Here the closed loop system given by (11) is considered as a polytopic system [25] and the stability analysis is performed using a quadratic Lyapunov function $V(x) = x^T Px$. The stability conditions are given in the form of a set of LMI to satisfy.

The model may be represented as follows:

$$\begin{cases} \dot{x}(t) & = & A(\mu(t))x(t) + Br(t), \\ A(\mu(t)) & = & \sum_{i=1}^N \mu_i(t)A_i, \ \forall i, \ \mu_i(t) \geq 0, \\ & & \sum_{i=1}^N \mu_i(t) = 1. \end{cases} \quad (12)$$

where $N = 2$, with $A_1 = A(\underline{w})$ and $A_2 = A(\overline{w})$.

The stability theorem of this class of system is given by:

Theorem 1: If it exist a matrix $P = P^T > 0$ such that

$$A_i^T P + PA_i < 0, \quad \forall i = 1, \ldots, N \quad (13)$$

then, the closed loop (12) is asymptotically stable.

The proof is obvious considering the results of [25].

IV. APPLICATION

In this section, the stability and the robustness of the closed loop is analyzed by considering the stepper motor test bench developed in LAGIS at École Centrale de Lille (see Fig. 3). The motor parameters have been identified in [24]: $R = 2.86\Omega$, $L = 10.2mH$, $K_c = 0.26N.m.A^{-1}$, $F_v = 2.37.10^{-4}N.m.S.rad^{-1}$, $J = 3.18.10^{-4}kg.m^2$ and $w(t) \in [-15,\ 15]rad.s^{-1}$.
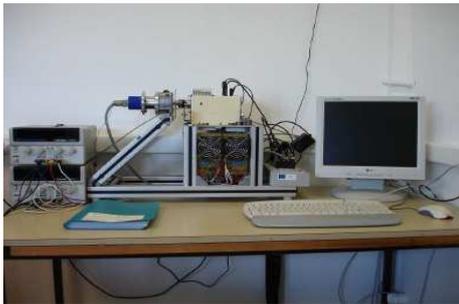
Fig. 3. Stepper-motor test bench.

A. Stability Analysis

Consider the closed loop (12) with the controller parameters $\tau = 0.001$, $n = 2$ and the desired closed loop dynamic $\ddot{y}(t) = -100y(t) - 20\dot{y}(t) + 100r(t)$ i.e. $K = [100\ 20]$. By using MatLab/SeDuMi [26] as solver and YALMIP [27] as parser in MATLAB®, a feasible solution for *Theorem 1* LMI conditions is obtained. This ensures the closed loop stability.

B. Experimental result

The results obtained on the LAGIS test bench (see Fig. 3) are presented in Figure 2. This figure shows the evolution of the PMSM position $\theta(t)$ and the ideal closed loop output θ_{ref} (solutions of $\ddot{y}(t) = -k_0y(t) - k_1\dot{y}(t) + k_0r(t)$) for different values of τ and k_i. It appears clearly that for smaller values of τ the tracking error E_t is closer to zero. Considering small enough τ allows to follow any specified dynamic (k_0, k_1) but the control signal v_q is more affected by noises and may be more susceptible to saturate. Despite that the controller is derivative based, the noises affecting the control signal are low and acceptable.
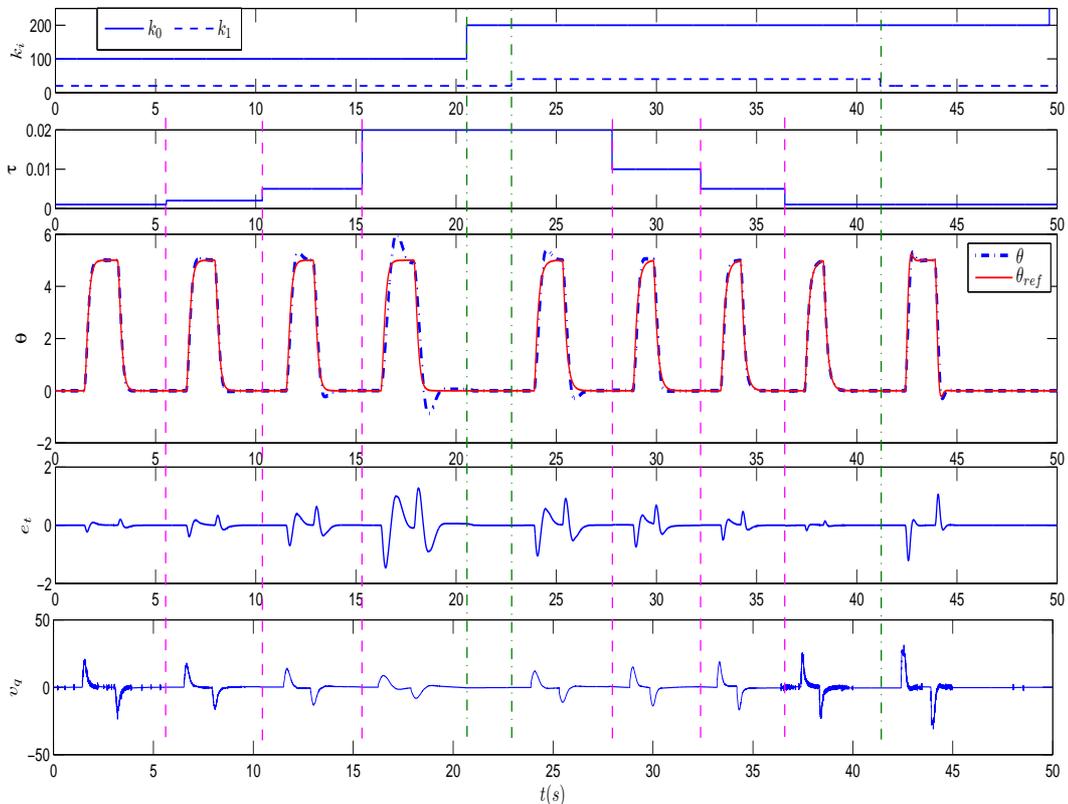

Fig. 2. Experimental results on the PMSM showing the evolution of the output $\theta(t)$, the specified dynamic $\theta_{ref}(t)$, the tracking error E_t and the control signal v_q for different value of the controller parameter

V. Robustness Analysis

In order to show the robustness of this controller, we consider two cases: The first case considers time varying uncertainties on the PMSM parameters. The second case considers a bad choice on the controller parameter $\hat{\alpha}$.

A. System Parameters Time Varying Uncertainties

For this example, consider that the controller parameters are $\tau = 0.01$, $K = [100 \; 20]$ and $\hat{\alpha} = K/(JR)$ (K, J and R being the parameters nominal values). The PMSM parameter (7) uncertainties are now considered with the following system matrix $A_m(t)$:

$$A_m(t) = \begin{pmatrix} -p_3(t) & n_p w(t) & 0 & 0 \\ -n_p w(t) & -p_3(t) & -p_4(t) & 0 \\ 0 & p_1(t) & -p_2(t) & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix},$$

where the time varying parameters are:
- $p_1(t) \in [0.9 * K/J \quad 1.2 * K/J]$ represents the time varying uncertainty on K/J,
- $p_2(t) \in [0.9 * F_v/J \quad 1.2 * F_v/J]$ represents the time varying uncertainty on F_v/J,
- $p_3(t) \in [R/L \quad 1.2 * R/L]$ represents the time varying uncertainty on R/L,

- $p_4(t) \in [K/L \quad 1.02 * K/L]$ represents the time varying uncertainty on K/L.

Since the matrix $A_m(t)$ is bounded, it is easy to obtain a convex hull vertices [25] A_i, $i = 1, \ldots, N$ such that $A(t) \in conv(A_1, \ldots, A_N)$. Here $N = 2^5$ because the matrix $A_m(t)$ has 5 independent time varying parameters ($w(t)$ and $p_i(t)$). Because the LMI problem of *Theorem* 1 with these matrices has a feasible solution, then PMSM in closed loop is stable despite the time varying uncertainties.

Note that the results provided here are not optimized. By considering different values of τ and $\hat{\alpha}$ or by considering more general Lyapunov functions [28], [29], these uncertainties can be considered larger.

B. Bad Tuning Of $\hat{\alpha}$

For this case, consider that that the controller parameters are $\tau = 0.01$ and $K = [100 \; 20]$, and that the parameter $\hat{\alpha}$ has an uncertainty of ± 20. By following the same approach as the previous section, the LMI problem of *Theorem* 1 with the appropriate matrices has a feasible solution so the PMSM in closed loop is stable despite the bad tuning of the parameter $\hat{\alpha}$.

Another important point concerns the system robustness and the estimation of the parameter α. Figure 4
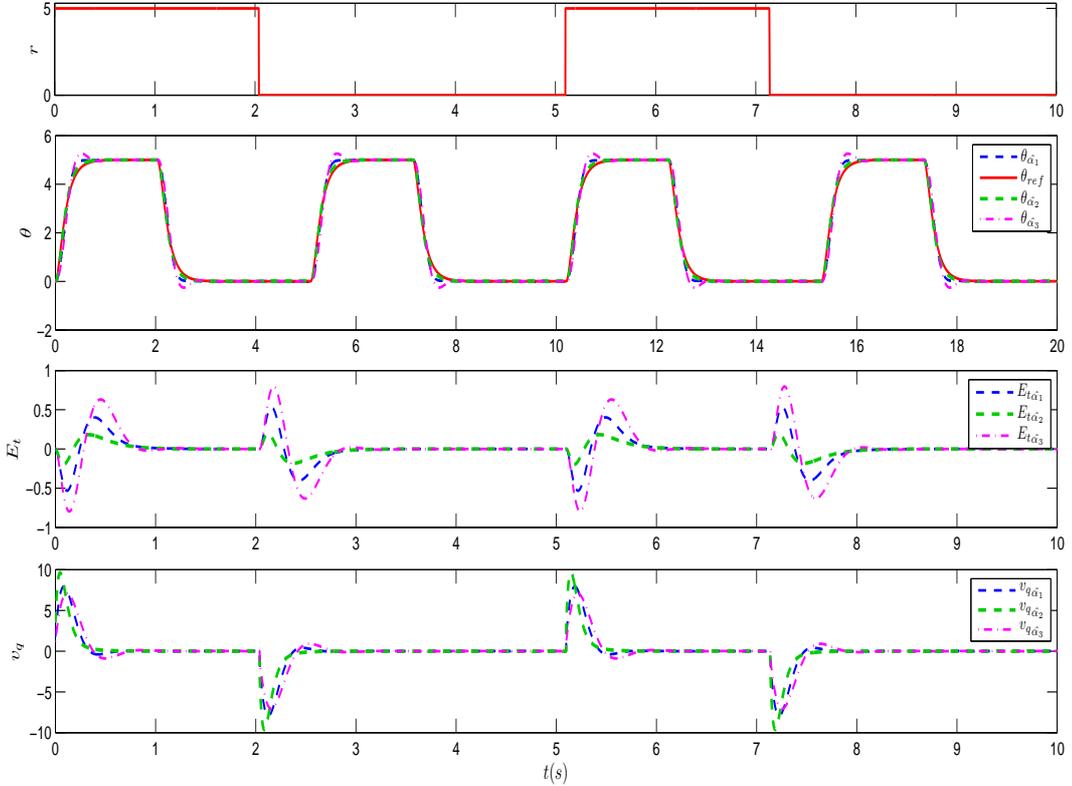

Fig. 4. Simulation results on the PMSM showing the evolution of the output $\theta(t)$, the specified dynamic $\theta_{ref}(t)$, the tracking error E_t and the control signal v_q for different approximation of α such that $\hat{\alpha}_1 = 0.5\alpha$, $\hat{\alpha}_2 = \alpha$ and $\hat{\alpha}_3 = 1.5\alpha$

shows that even if there is some mismatch between this parameter and its estimation $\hat{\alpha}$, the stability and the specified dynamic tracking can be guaranteed.

VI. Conclusion

This paper proposed a method to design dynamic output controller. In contrast of observer based controllers, the proposed controller allows the stabilization of LPV systems even if the time varying parameters are not measured. An application to the Permanent Magnet Synchronous Motors stabilization with uncertainties is proposed. This application shows the good tracking properties of this controller and the simplicity of its tuning. Our future work will deal with extended the class of system (multi-input multi-output, zero dynamics), guaranteed performances and noise rejection.

References

[1] D. Huang and S. K. Nguang, "Static output feedback controller design for fuzzy systems: An ilmi approach," *Inf. Sci.*, vol. 177, no. 14, pp. 3005–3015, 2007.

[2] B. Mansouri, N. Manamanni, K. Guelton, A. Kruszewski, and T. M. Guerra, "Output feedback lmi tracking control conditions with h_∞; criterion for uncertain and disturbed t-s models," *Inf. Sci.*, vol. 179, no. 4, pp. 446–457, 2009.

[3] M.Sato, "Gain-scheduled output-feedback controllers depending solely on scheduling parameters via parameter-dependent lyapunov functions," *Automatica*, vol. 12, pp. 2786–2790, 2011.

[4] K. Tanaka, T. Ikeda, and H. Wang, "Fuzzy regulators and fuzzy observers: relaxed stability conditions and lmi-based designs," *IEEE Transactions on Fuzzy Systems*, vol. 6, no. 2, pp. 250–265, 1998.

[5] A. Sala, T. Guerra, and R. Babuška, "Perspectives of fuzzy systems and control," *Fuzzy Sets Syst.*, vol. 156, no. 3, pp. 432–444, 2005.

[6] K. Åström and T. H. ägglund, *Advanced PID Control*. ISA - The Instrumentation, Systems, and Automation Society; Research Triangle Park, NC 27709, 2006.

[7] A. Khodabakhshian and M. Edrisi, "A new robust {PID} load frequency controller," *Control Engineering Practice*, vol. 16, no. 9, pp. 1069 – 1080, 2008.

[8] A. Van der Schaft, *L2-Gain and Passivity Techniques in Non-linear Control*. Springer, 1996.

[9] B. Zhang and Q. Han, "Robust sliding mode h_∞; control using time-varying delayed states for offshore steel jacket platforms," *IEEE International Symposium on Industrial Electronics*, pp. 1–6, 2013.

[10] S. Li, L. Xiaodong, L. Yong'an, Z. Lilin, and H. Zhengping, "Research on robust h_2/h_∞; optimization control for unified power quality conditioner in micorgrid," *International Power Electronics and Motion Control Conference*, vol. 4, pp. 2864–2867, 2012.

[11] Y. Watanabe, I. Takami, and G. Chen, "Tracking control for 2dof helicopter via robust lq control with adaptive law," *Control Conference*, pp. 399–404, 2012.

[12] Y. Watanabe, N. Katsurayama, I. Takami, and G. Chen, "Robust lq control with adaptive law for mimo descriptor system," *Asian Control Conference*, pp. 1–6, 2013.

[13] J. Stecha and J. Roubal, "Lq and dead beat control combination from the set of stabilizing controllers," *Mediterranean Conference on Control and Automation*, pp. 895–900, 2008.

[14] J. Cédric, J. Masse, and M. Fliess, "Étude préliminaire d'une commande sans modèle pour papillon de moteur ..... A model-free control for an engine throttle: a preliminary study," *Journal Européen des Systèmes Automatisés*, vol. 42, no. 2-3, pp. 337–354, 2008.

[15] H. Abouaissa, M. Fliess, V. Iordanova, and C. Join, "First steps towards a model-free control of a freeway traffic flow—Prolégomènes à une régulation sans modèle du trafic autoroutier," *Conférence Méditerranéenne sur l'Ingénierie Sûre des Systèmes Complexes* , 2011.

[16] P. Gédouin, E. Delaleau, J. Bourgeot, C. Join, S. Arbab-Chirani, and S. Calloch, "Experimental comparison of classical pid and model-free control: position control of a shape memory alloy active spring," May 2011.

[17] B. D. Novel, C. Boussard, M. Fliess, O. E. Hamzaoui, H. Mounier, and B. Steux, "Commande sans modèle de la vitesse longitudinale d'un véhicule électrique," in *Sixième Conférence Internationale Francophone d'Automatique*, 2010.

[18] M. Mboup, "Parameter estimation for signals described by differential equations," *Applicable Analysis*, vol. 88, no. 1, pp. 29–52, 2009.

[19] J. Slotine, "Sliding controller design for non-linear systems," *International Journal of Control*, vol. 40, no. 2, pp. 421–434, 1984.

[20] M. N. Nounou, H. N. Nounou, and M. S. Mahmoud, "Robust adaptive sliding-mode control for continuous time-delay systems," *IMA Journal of Mathematical Control and Information*, vol. 24, no. 3, pp. 299–313, 2007.

[21] X. Yan, S. Spurgeon, and C. Edwards, "Robust sliding mode observer with parameters estimation for a class of nonlinear time-delay systems," *IEEE Conference on Decision and Control*, pp. 96 –101, 2010.

[22] Y. Feng and L. Wang, "Terminal sliding mode observer based parameter estimation method for permanent magnet synchronous motor control system," *International Workshop on Variable Structure Systems*, pp. 184–189, 2010.

[23] S. Maalej, A. Kruszewski, and L. Belkoura, "Derivative based control for ltv system with unknown parameters," *European Control Conference*, 2013.

[24] R. Delpoux, M. Bodson, and T. Floquet, "Parameter estimation of permanent magnet stepper motors without position or velocity sensors," in *American Control Conference*, 2012.

[25] E. F. S. Boyd, L. El-Ghaoui and V. Balakrishnan, "Linear matrix inequalities in system and control theory," *SIAM*, vol. 15, pp. 23–24, 1994.

[26] J. F. Sturm, "Using sedumi 1.02, a matlab toolbox for optimization over symmetric cones," *Optimization Methods and Software*, vol. 11, no. 1-4, pp. 625–653, 1999.

[27] J. Lofberg, "Yalmip : a toolbox for modeling and optimization in matlab," *IEEE International Symposium on Computer Aided Control Systems Design*, pp. 284–289, 2004.

[28] M. Asemani, V. Majd, and S. Mobayen, "A multiple lyapunov function approach for robust h_∞; observer-based tracking control of uncertain t-s fuzzy systems," *International Conference on Control, Instrumentation and Automation*, pp. 367–372, 2011.

[29] W.-R. Horng, C.-H. Fang, C.-H. Lee, and J.-H. Chou, "H2 guaranteed cost of uncertain continuous t-s fuzzy systems by multiple lyapunov function approach," *IEEE International Conference on Fuzzy Systems*, pp. 1380–1387, 2011.