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Model-free and Adaptive Control of a DC Motor: A Comparative Study

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***Abstract*— The present paper proposes the recent Model-free Control (MFC) approach applied to a position control scheme for a DC motor with uncertainties and unmodeled dynamics. This novel technique guarantees a fast algebraic on-line dynamics estimation for ultra-local model identification. It grants to keep out of complicated task of non-linear mathematical system modeling and leads to an explicit gain tuning. Comparisons are carried out between the proposed approach and the classical adaptive controller. Computer simulations have been verified using MATLAB/ Simulink.**

Keywords*— *Model-free Control, intelligent PID controllers, Estimation, Adaptive Control

I. Introduction

DC motors are convenient for numerous applications, inclusive of turntables, conveyors and others for which adjustable position and speed are desired. A high performance characteristics is required in all industrial applications [1]. In many practical implementations it may not be efficient and reasonable to measure all state variables. The alternative perspective is to use an estimation technique to estimate these state variables which are not measured, and being used later in the implementation of the feedback controller [2].

The author in [3] applied a classical approach using the system model which is investigated almost generally, and enhanced the control performance by an adaptive control technique [4].

Recently, Model-Free Control (MFC) technique is developed by M. Fliess and C. Join [5], based on an ultra-local model that is continuously updated on the report of the input-output behavior. It is designed to take control of the uncertainties and system unmodeled dynamics for linear systems as well as nonlinear systems. Research is being processed on the effect of the MFC on magnetic levitation system [6], Hybrid unmanned aerial vehicles (UAVs) [7], active magnetic bearing [8], vehicles brake system control [9].

In this article we set out an asymptotic algebraic method using MFC, which covers the execrably known parts of the plant along with the distinct possible disturbances, not requiring to make any notability between them in order to implement a control scheme.

The objective of this paper is to investigate the efficiency of the Model-Free Controller (MFC) over the classical adaptive controller on DC motor position control.

This paper is structured as follows: Section 2 presents the used DC motor model and the problem statement. Section 3 presents a general review of MFC approach and its control design for a DC motor with coulomb friction effects. For comparison, an adaptive control technique is also presented. In Section 4, simulation results are presented. Finally, a conclusion is devoted to concluding remarks.

II. Motor Model

In this section, we first recap the linear model of the DC Motor.

A. Physical setup

The main dynamic equation of the DC motor system is acquired by Newton's Second Law:

$$kV = J\ddot{\theta}_m + v\dot{\theta}_m + \hat{\Gamma}_c(\dot{\theta}_m) \quad (1)$$

Where, v is the viscous friction coefficient (N m s), J is the inertia of the motor (kg m^2), k is the electromechanical constant (N m / V). $\theta_m(t)$ stands for the angular position of the motor (rad), $\ddot{\theta}_m$ is the acceleration of the motor (rad/s^2) and $\dot{\theta}_m$ is the velocity (rad/s).

This linear model is affected by an unknown perturbation $\hat{\Gamma}_c$ (N m) input caused by Coulomb friction effects [10], which depends only on the sign of the angular velocity of the motor (the case when the motor rotates) of the form $\mu sign(\dot{\theta}_m)$ where, μ is a constant, and when the velocity is null the friction counteract to the torque generated by the input voltage with respect on its sign.

B. Problem statement

For a stated appropriate smooth reference trajectory $\theta_m^*(t)$ for a position tracking of the DC motor described previously by the dynamics presented in (1), and taking in consideration the supposedly signal input noisy measurements, V, and of the

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output signal, $\theta_m(t)$, in addition to the presence of unknown nonlinear effects produced by Coulomb friction or model parametric uncertainties, the feedback controller have to undertake the asymptotic tracking of $\theta_m^*(t)$ exactly by the system output $\theta_m(t)$.

III. CONTROLLER DESIGN FOR THE DC MOTOR

A. Model-free control (MFC) approach overview

Given n[th] order nonlinear SISO system:

$$y^{(n)} = f\left(y, \dot{y}, \ldots, y^{(n)}\right) + \alpha u \quad (2)$$

Where, u is the system input, α is unknown input factor and $f(.)$ is the modeled system dynamics.

The uncertainties and un-modeled dynamics with the unknown input factor may be represented in the system as f_e:

$$f_e(.) = Model\ Uncertainties + (\alpha - \beta)u \quad (3)$$

Consequently, the system can be written as follows:

$$y^{(v)} = f(.) + f_e(.) + \beta u \quad (4)$$

Where, v is represents the order of the expected model, and β is the estimate of the unknown scaling factor α that is going to be selected by the practitioner to ensure a certain control performance.[11]

The input-output relationship is then represented by an ultra-local model that is continuously updated:

$$y^{(v)} = F + \beta u \quad (5)$$

Where, F is a constantly updated parameter that represents the overall dynamics of the system $f(.) + f_e(.)$, and it may be approximated to reduce the noise generated by the derivative $y^{(v)}$.[5]

$$F = y^{(v)} - \beta u \quad (6)$$

Take note that the parameter of estimation is valid for a short period of time and it must be constantly updated [5]. Generally, the model-free control signal may have the following form:

$$u = -\frac{F - y_d^{(v)} + u_c}{\beta} \quad (7)$$

Where, $y_d^{(v)}$ is the v^{th} derivative of the reference trajectory, and u_c is the control signal of the feedback controller.

Substituting then (7) in (6),

$$y^{(v)} = F + \beta\left(-\frac{F - y_d^{(v)} + u_c}{\beta}\right) = y_d^{(v)} - u_c \quad (8)$$

That being so,

$$y^{(v)} - y_d^{(v)} + u_c = 0 \quad (9)$$

$$e^{(v)} + u_c = 0 \quad (10)$$

Where, $e^{(v)}$is the v^{th} derivative error of ($e = y - y_d$), and u_c have to be chosen to undertake the linear differential equation that is asymptotically converged to the require trajectory. [5]

The practitioner has to pick a fitting value of v which is always chosen to be quite low, i.e., 1, or, rarely, 2, depending on the system stability and the feedback controller type utilized in the system.

To make this assertion evident, let $v=1$, thus (10) will be as follows:

$$\dot{e} + u_c = 0 \quad (11)$$

A first order differential equation may be expressed, if PD or P controller is implemented:

$$\dot{e} + K_p e + K_D \dot{e} = 0 \quad (12)$$

Likewise, if $v=2$, then a second order differential equation may be expressed, if PID or PD controller is used:

$$\ddot{e} + K_D \dot{e} + K_p e + K_I \int e = 0 \quad (13)$$

Fig. 1 illustrates a MFC scheme for a single-input single-output system while $v = 1$.

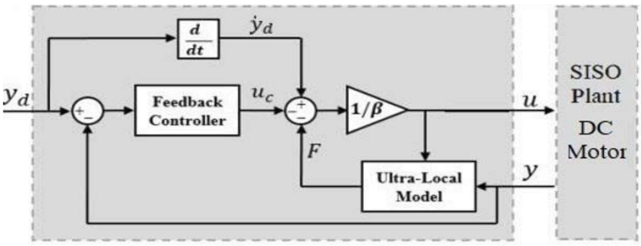

Figure 1 MFC design

As Fig. 1 exhibits, the ultra-local model in (5) will evaluate the value of the parameter F on every single iteration of the feedback controller. The system un-modeled dynamics will be estimated by updating the value of F, and set a suitable control input to the DC motor plant.

Remark: The measured output "y", the desired input "y_d", the control signal "u" represents: "$\theta_m(t)$", "$\theta_m^*(t)$", "V" respectively in (1).

1) Online estimation of the parameter F

Taking Laplace transform on the ultra-local model in (5) where, $v=1$ and assuming that F is constant for a short period of time:

$$sY(s) - y(0) = \frac{F}{s} + \beta \mathrm{U}(s) \quad (14)$$

Differentiating with respect to s in order to eliminate $y(0)$:

$$Y(s) - s\frac{d}{ds}Y(s) = -s^{-2}F + \beta\frac{d}{ds}\mathrm{U}(s) \quad (15)$$

Then, multiplying by $\frac{1}{s^2}$ for filtering and eliminating the time derivatives, by letting every component being integrated at least once to have a low-pass filters which attenuate noises:

$$\frac{1}{s^2}Y(s) + \frac{1}{s}\frac{d}{ds}Y(s) = -\frac{1}{s^{-4}}F + \beta\frac{1}{s^3}\frac{d}{ds}\mathrm{U}(s) \quad (16)$$

Using the inverse Laplace transform properties and classic rules of operational calculus, the resulting expression of (16) in time domain will be:

$$F = \frac{-6}{t^3}\int_0^t (t - 2\tau)y(\tau)d\tau - \frac{6\beta}{t^3}\int_0^t \tau(t - \tau)u(\tau)d\tau \quad (17)$$

The above expression can be digitally implemented using FIR filter.[12]

For the ultra-local model in (5), the estimation of the derivative $y^{(v)}$ (i.e., $v=1$) is achieved using distinct de-

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noising approaches [8] [11] [13]. For straightforwardness, low-pass filters are used in the coming simulations to reduce the produced noisy signals by the numerical differentiation.

2) Control law / PD tuning

Consider that $v = 1$ in (5):

$$\dot{y} = F + \beta u \tag{18}$$

Closing the loop as in Fig. 1 including a *PID* controller:

$$u = \frac{-F+\dot{y}_d-K_I\int e-K_P e-K_D\dot{e}}{\beta} \tag{19}$$

Where, y_d is the desired trajectory, $e = y - y_d$ is the tracking error and K_I, K_P, K_D are the frequent *PID* tuning gains.

Choosing $K_I = 0$, $K_P = \lambda^2$ and $K_D = 2\lambda$, λ € R^+ results in a stable closed loop system with two real negative poles ($-\lambda$):

$$\ddot{e} + \lambda^2 e + 2\lambda\dot{e} = 0 \tag{20}$$

B. Closed-loop adaptive PD controller

This subsection is devoted for the second approach which is the adaptive control technique.

Consider the second order perturbed system given in (1). supposing that J and v are unknown parameters and they are not linearly identifiable. Then, the parameter K / J could be denoted by A and the parameter v /J denoted by B are linearly identifiable. Considering the fact that $K=k /n$, where n is the is the reduction ratio of the motor, $\Gamma^* = \frac{\hat{\Gamma}_c}{nJ}$ and after some mathematical rearrangements, we obtain:

$$AV = \ddot{\hat{\theta}}_m + B\dot{\hat{\theta}}_m + \Gamma^* \tag{21}$$

1) The Procedure of Algebraic Identification

Firstly, we proceed to identify the unknown system parameters A and B as follows:

- The last above expression is multiplied on both sides by s^{-1}, to have a second linear equation for just A, and B. These parameters can be easily acquired by solving the resulted linear equations.
- Using operational calculus in (21) and taking the third derivative with respect to the complex variable s, we obtain an independent of initial conditions formula [3].
- Multiplying both sides of the resulting expression by s^{-3} in order avoid derivations.

Thus, we obtain the following Eq:

$$B\left(s^{-1}\frac{d^3\theta_m(s)}{ds^3} + 6s^{-2}\frac{d^2\theta_m(s)}{ds^2} + 6s^{-3}\frac{d\theta_m(s)}{ds}\right) - A\left(s^{-2}\frac{d^3V(s)}{ds^3} + 3s^{-3}\frac{d^2V(s)}{ds^2}\right) = -[\frac{d^3\theta_m(s)}{ds^3} + 9s^{-1}\frac{d^2\theta_m(s)}{ds^2} + 18s^{-2}\frac{d\theta_m(s)}{ds} + 6s^{-3}\theta_m(s)] \tag{22}$$

Back to the time domain, the linear equation of the unknown parameters A and B can be expressed as:

$$Bp_{11}(t) - Ap_{12}(t) = -q_{11}(t) \tag{23}$$

Where,

$$p_{11}(t) = -\int t^3\theta_m + \iint t^2\,\theta_m - 6\iiint t\theta_m \tag{24}$$

$$p_{12}(t) = -\iint t^3 V - 3\iiint t^2 V \tag{25}$$

$$q_{11}(t) = -t^3\theta_m - 9\int t^2\theta_m + 18\iint t\,\theta_m - 6\iiint \theta_m \tag{26}$$

Equation (22) is multiplied on both sides by s^{-1} once more, this leads to a second order linear equation for the estimation of A, and B, such that:

$$p_{21}(t) = \int p_{11}\ ,\ p_{22}(t) = \int p_{12}\ ,\ q_{21} = \int q_{11}$$

This linear system can be represented in matrix form as:

$$PX = Q \tag{27}$$

where, P is a matrix composed of time dependent coefficients, X is a column vector of the parameters B and A, and Q is also a column vector with time dependent coefficients. Its general form is given by:

$$\begin{bmatrix} p_{21} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}\begin{bmatrix} B \\ A \end{bmatrix} = \begin{bmatrix} q_{11} \\ q_{21} \end{bmatrix} \tag{28}$$

Finally, the estimation of the parameters A and B can be easily obtained by solving the following linear equations:

$$A = \frac{-p_{21}(t)p_{11}(t)+p_{11}(t)q_{21}(t)}{p_{11}(t)p_{22}(t)-p_{12}(t)p_{21}(t)} \tag{29}$$

$$B = \frac{p_{22}(t)q_{11}(t)-p_{12}(t)q_{21}(t)}{p_{11}(t)p_{22}(t)-p_{12}(t)p_{21}(t)} \tag{30}$$

Secondly, we proceed to Identify the Coulomb's friction coefficient, by considering the system given in (21), where, $\Gamma^* = \mu sign(\dot{\hat{\theta}}_m)$, such that μ is the scaled coulomb's friction amplitude. Then, we can identify the perturbation term $\mu sign(\dot{\hat{\theta}}_m)$ produced by the Coulomb's friction torque using this expression:

$$\mu sign\left(\dot{\hat{\theta}}_m\right) = AV - \ddot{\hat{\theta}}_m - B\dot{\hat{\theta}}_m \tag{31}$$

2) Control law / PD tunig

A *PD* controller is designed by replacing the closed-loop poles of the system in Fig. 2 in faraway location of the negative real axis: $-\alpha$ with $\alpha > 0$, such that, $C_{PD}(s) = k_p + k_D s$ where, k_P, k_D are the gains. If the motor system has initial values A_0 and B_0, thus, the stability condition of the closed-loop formula $(1 + G_{motor}(s)C_{PD}(s))$ leads to have the following characteristic polynomial:

$$s^2 + (k_D A_0 + B_0)s + k_p A_0 = 0 \tag{32}$$

Identifying the above coefficients of the closed-loop characteristic polynomial (32) with those of a desired second-order Hurwitz polynomial by using the bellow desired second-order polynomial:

$$P(s) = (s+\alpha)^2 = s^2 + 2\alpha s + \alpha^2 \tag{33}$$

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Where, α represents the location of the closed-loop poles. Equating the identical terms of the equations (32) and (33), the tuning gains k_{P0} and k_{D0}, which depend on the system parameters, could be obtained by computing the following expressions:

$$k_{p0} = \frac{\alpha^2}{A_0} \text{ , } k_{v0} = \frac{2\alpha - B_0}{A_0} \quad (34)$$

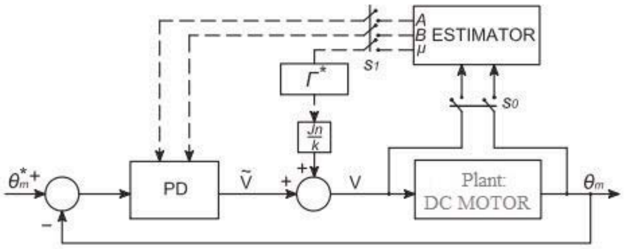

Figure 2 Adaptive control scheme

Fig. 2 depicts the closed-loop feedback adaptive control system. At time t_0, by switching ON s_0, the estimator is initiated. In a short duration t_1, the algebraic estimator evaluates the parameter values A, B and $\hat{\Gamma}_c = \mu nJ$ of the DC motor. then, the *PD* controller is permanently updated, by switching ON s_1, the new updated adaptive controller has the subsequent gains:

$$k_P = \frac{\alpha^2}{A} \text{ , } k_D = \frac{2\alpha - B}{A} \quad (35)$$

For the estimation of Coulomb's friction, $\hat{\Gamma}_c$, a compensation term is injected in the system to eliminate the effect of this disturbance. The compensation term is added in the control input signal to the plant such that:

$$V = \tilde{V} + \Gamma^* \frac{Jn}{k} \quad (36)$$

Where, $\tilde{V}$ is the control voltage produced by the controller, and $\Gamma^* \frac{Jn}{k}$ is the introduced voltage to compensate the Coulomb friction effect. When $\dot{\theta}_m > 0$, Γ^* is evaluated by the form $\Gamma^* = \mu sign(\dot{\theta}_m)$. In the other hand, when $\dot{\theta}_m = 0$, the voltage to the motor may be different from null value, there is a constant friction torque counteract to the torque produced by the control signal. That effect is attenuated by computing the compensation term as $\Gamma^* = \mu sign(V)$.

IV. Simulation Results

This section is devoted to show that computer simulations were accomplished with a view to verify the performance of the proposed control techniques.

A) Parameters of the DC Motor

The DC motor used is of type RH-8D-6006-E036AL-SP(N) which has the following description:

- Electromechanical constant $k = 0.21(\text{N m /V})$.
- Inertia $J = 6.87 * 10^{-5}(\text{kg m}^2)$.
- Viscous friction $v = 1.041 * 10^{-3}(\text{N m s})$.
- Coulomb friction coefficient $\xi = \mu nJ = 0.119(\text{N m})$
- Reduction ration *n=50*.

The motor shaft may turn either left or right around the vertical axis.

B) Simulation results of the adaptive controller

The transfer function considered for the PD controller was set as $PD(s) = k_P + k_D$ with gains $\{k_P, k_D\}$ that are designed to place the closed loop poles in a faraway location of the negative real axis, say -120, setting A_0=150 and B_0 =0.5 as initial values. Thus, the parameters values obtained of the *PD* controller are: k_{P0} =96 and k_{D0} =1.60. The desired trajectory evolution used for the position tracking problem of the DC motor is defined as a sinusoidal input with an amplitude of 1 and a frequency of 1 (rad/s). When the switch s_0 is ON at time t_0=0.16 (s) The control system depicted in Fig. 2 begins to elaborate with the *PD* controller with initial values k_{P0} and k_{D0}. At time t =t_0+0.16 (s) good estimation of the motor parameters are obtained:

A=61.13 (N/ (V kg s)) and B =15.15 (N s/ (kg m)) (see Fig. 3 and 4).

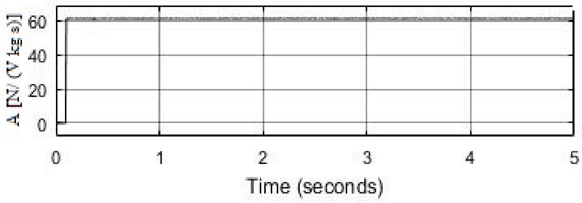

Figure 3 Estimation of the parameter *A*

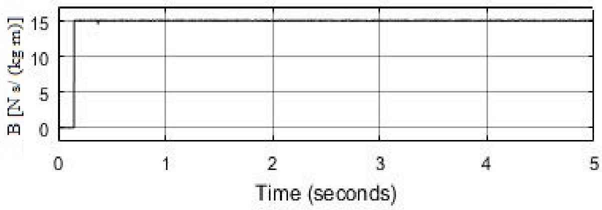

Figure 4 Estimation of the parameter *B*

By switching ON the switch s_1 at time t_1 =0.35 (s) the *PD* controller is updated with these new estimated parameters, k_P =368.1 and k_D =1.75. Fig. 5 depicts the scaled Coulomb's friction coefficient instantaneously evaluated after the estimation of the parameters *A* and *B*. μ = 34.72 ((N m)/ (kg m^2)). The compensation voltage term is evaluated at time t_1 as shown in (36), Γ^* = 1.25 (V).

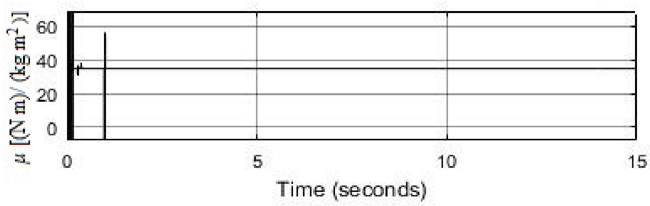

Figure 5 Coulombs friction coefficient μ estimation

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Fig. 6 shows the evolution of the tracking error. Fig. 7 illustrates the Sinusoidal trajectory tracking using the *PD* adaptive controller. Noting that until t_1 =0.35 (s), the error is high when the controller is operating with the initial values. Fig. 8 depicts the control signal to the DC motor. As Noted previously that at time 0.35 (s), a peak in the control signal is produced by the update of the controller. After this time, the control signal is noisier for the reason that this signal contains the friction compensating term. In fig. 9 we add a perturbation signal that is high enough to distort the input signal in order to observe the smoothing effect of the controller.

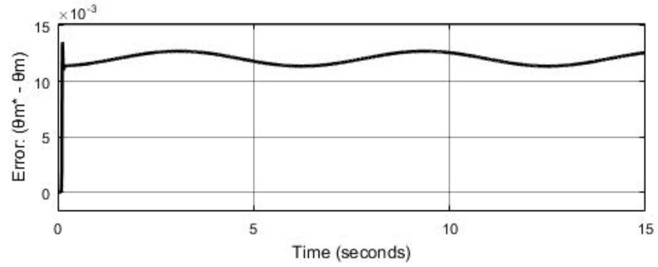

Figure 6 Evolution of the tracking error using adaptive controller

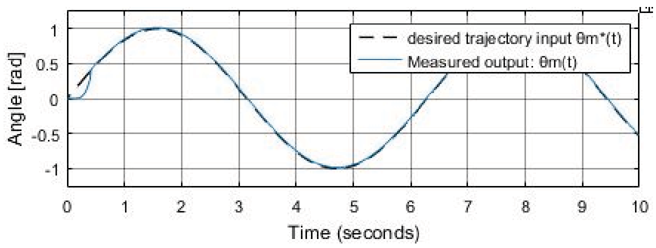

Figure 7 Sinusoidal trajectory – evolution of the DC motor, using adaptive control

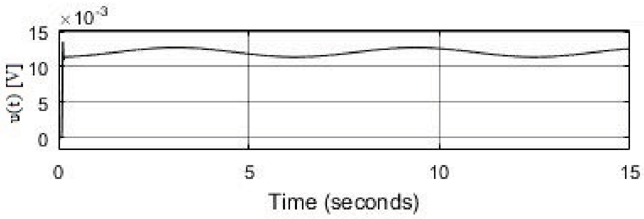

Figure 8 Control signal u(t), using adaptive control

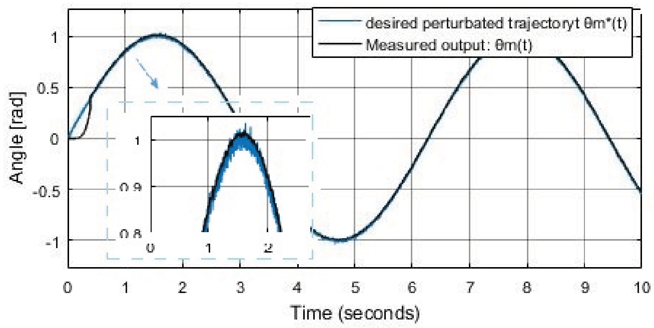

Figure 9 Perturbated Sinusoidal trajectory – evolution of the DC motor, using adaptive control

C) Simulation results of the model-free controller

In the subsequent simulations, the parameter v in (6) is set to be equal to 1, then,

$$y^{(1)} = F + \beta u \qquad (37)$$

Where, y represents the measured output of the DC motor system model which is θ_m for this case study, and y_d represents θ_m^* (the desired trajectory tracking) (see Fig. 1).

For comparison purpose, as set previously the desired reference trajectory used for the tracking problem of the DC motor is specified as a sinusoidal input with an amplitude of 1 and a frequency of 1 (rad/s). *F*, which is a continuously updated parameter, it subsumes the poorly recognized parts of the plant, as well as the various possible disturbances, without the need to make any distinction between them, it is approximated by a piecewise constant function as shown in Fig 10.

Measurements are usually noisy. Therefore, using a filter is extremely recommended. the derivative estimator is a way to express the estimator *F* as an integral over a short interval [t-T, t]. this integral is considered as a low pass filter (see [12] for more detail) , then equation (17) may take the form:

$$\hat{F} = \frac{-6}{T^3}\int_0^T (T-2\tau)y(\tau)d\tau - \frac{6\beta}{T^3}\int_0^T \tau(T-\tau)u(\tau)d\tau \qquad (38)$$

and can be represented in discrete form,

$$\widehat{F_k} = \frac{-6T_s}{(n_sT_s)^3}\sum_{i=0}^{n_s} \begin{matrix}[(n_s-2i)y((k-i)T_s)] - \\ \beta[i(n_s-i)u((k-i)T_s)]\end{matrix} \qquad (39)$$

Such that, $T = n_sT_s$ where, T is the estimation window, n_s is the number of samples ($n_s = 2000$), and T_s is the fixed sample time ($T_s = 0.0001$ s).

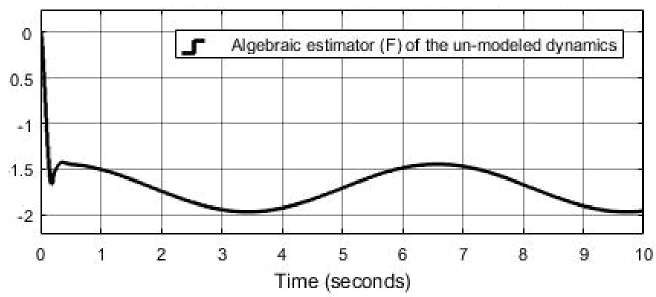

Figure 10 Algebraic estimator (*F*) of the un-modeled dynamics

The control law is applied to the system by choosing $\beta = 3$ taking into account that βu and $\dot{y}$ are of the same magnitude (detailed tuning procedure can be found in [9]). After closing the loop as in Fig. 1, including a Proportional-Derivative action (*i-PD*) and selecting $K_I = 0$, $K_P = \lambda^2$ and $K_D = 2\lambda$ where, $\lambda = \sqrt{6}$ then the control signal is generated as in Fig. 11, based on that the desired evolution of the DC motor position is shown in Fig. 12 as well as the tracking error in Fig. 13.

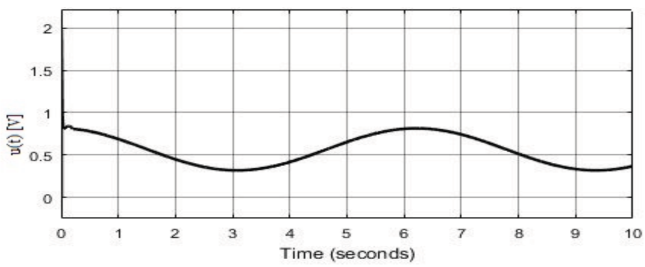

Figure 11 Control signal u(t), using MFC

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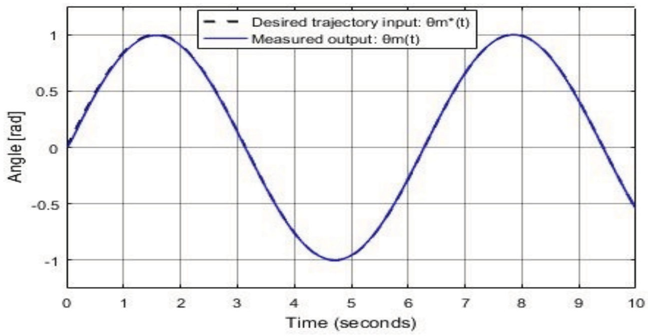

Figure 12 Sinusoidal trajectory – evolution of the DC motor, using MFC control approach

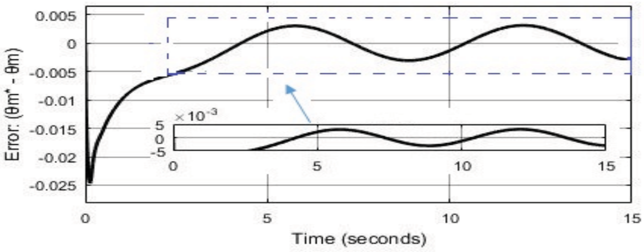

Figure 13 Evolution of the tracking error using MFC

Fig. 14 below depicts a noisy desired trajectory "$\theta_m{}^*$". It can be observed that the model-free controller neglects this perturbation in the output signal.

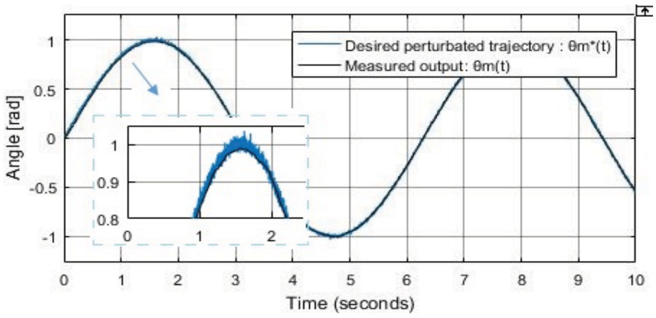

Figure 14 Perturbated Sinusoidal trajectory – evolution of the DC motor, using MFC

V. Conclutions

The simulation results exhibit that the estimation procedure for identifying several parameters of the DC motor dynamics system model (takes few seconds) along with its application in the adaptive control approach have carried out effectively on the DC motor. A challenging problem is put aside if the system model has higher order or being nonlinear then the mathematical modeling become very complicated to identify as well as using this identification in the control procedure. Whereas the online estimation using the ultra-local model grants to keep away of complicated tasks of mathematical system modeling and allows a real time update of the model without caring about the linearity of the system or identifying the distinct system parameters, just the value of the parameter F is enough to summarize all uncertainties and the un-modeled dynamics.

By virtue of MFC design action, the *PID* tuning gains procedure becomes easier than classic techniques.

It's interesting to notice too that model-free control provided a precise tracking performance, starting from the transient response that is very fast in time (few milliseconds) and robust in proportion to the Coulomb friction disturbances as well as the perfect smoothing of the perturbated reference trajectory, in addition to the very small tracking error compared to the adaptive control approach.

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