International Journal of Sciences and Techniques of Automatic control & computer engineering
IJ-STA, Volume 5, N° 1, June 2011, pp. 1472–1485.

Adaptive Generalized Predictive Control of a Separately Excited DC Motor

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Abstract. *In this paper, the Adaptive Generalized Predictive Control (GPC) is designed to control a separately excited DC motor. The model of the process has been obtained by using on-line identification technique to identify a model for the dynamic behavior between the armature voltage input and the speed of a DC motor. The standard (GPC) algorithm is presented. A Single Input Single Output (SISO) model is used for control purposes. The model parameters are estimated on-line using a Recursive Least Squares (RLS) algorithm. The performance of the proposed Adaptive Generalized Predictive Controller is illustrated by a simulation example of a separately excited DC motor. Obtained results have shown better characteristics concerning both set point tracking and disturbance robustness for adaptive predictive control.*

Keywords. *Adaptive control, Generalized Predictive Control, parameter estimator, separately excited DC motor.*

1. Introduction

The DC Motors are widely used in industries [1]. Hence, DC Motors are the important machine in the most control systems such as electrical systems in homes, vehicles, trains and aircrafts. It is well known that the mathematical model is very crucial for a control system design. For a DC motor, there are many models to represent the machine behavior with a good accuracy. However, the parameters of the model are also important because the mathematical model cannot provide a correct behavior without correct parameters in the model. Therefore, the parameters can be determined by iden-

This paper was recommended for publication in revised form by the editor Staff.
Edition: CPU of Tunis, Tunisia, ISSN: 1737-7749

tification technique. The on-line identification based on Recursive Least Squares (RLS) of Single Input Single Output (SISO) process has been applied to identify a separately excited DC motor.

This paper presents the application of Adaptive Generalized Predictive Control (GPC) to achieve set point tracking of the output of the plant. The GPC is one of the most favorite predictive control methods. This method is popular not only in industry, but also at universities. It was first published in 1987 [2] - [3]. The authors wanted to find one universal method to control different systems. The GPC is applicable to the systems with non-minimal phase, unstable systems in open loop, systems with unknown or varying dead time and systems with unknown order [4].

The aim of predictive control algorithm is to compute future control actions so that the systems output tracks the reference trajectory with minimal error. The cost function also contains a cost of control action increment.

The adaptive predictive control has been used to regulate the speed of separately excited DC motor by means of the armature voltage (control signal). It will be shown that the Adaptive Generalized Predictive Control offers better disturbance robustness and better set point tracking characteristics.

The objective of this paper is to design a SISO adaptive predictive controller of a separately excited DC motor. The paper is organized as follows: Section 2 deals with modeling of a separately excited DC motor. Section 3 presents the model identification of the process. In section 4 the derivation of the control law for the GPC is reviewed. Section 5 is devoted the description of the adaptive control algorithm. In section 6, the effectiveness and superiority of the adaptive system, is demonstrated by simulation example. Some concluding remarks end the paper.

2. Process modeling

The equivalent circuit of separately excited DC motor consists of independent two circuits, armature circuit and field circuit as shown in Figure 1 [1].

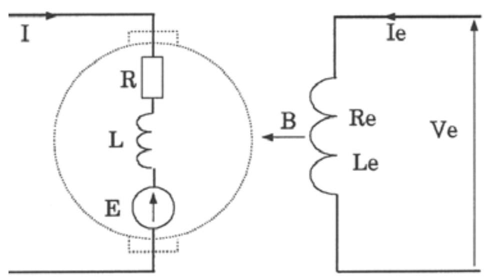

Fig. 1. The equivalent circuit of separately excited DC motor

The dynamic of the separately excited DC motor may be expressed by the following equations:
The armature voltage equation is written as:

$$E(t) = -RI(t) + U(t) - L\frac{dI(t)}{dt} \tag{1}$$

Setting E(t) in (1) equal to $K\Omega(t)$
The mechanical motion equation is given by:

$$C_m(t) = f\Omega(t) + \frac{Jd\Omega(t)}{dt} + C_r(t) \tag{2}$$

Setting $C_m(t)$ in (2) equal to $KI(t)$
Where,
K: the voltage constant.
R: the armature resistance.
L: the armature inductance.
J: the rotor mass moment of inertia.
f: the viscous friction coefficient.
$\Omega(t)$: the rotor speed.
I(t): the armature current.
U(t): the terminal voltage.
$C_r(t)$: the load torque.

Taking the Laplace transform, the above equations can be written as:

$$U(p) = RI(p) + E(p) + LpI(p) \tag{3}$$

$$C_m(p) = f\Omega(p) + Jp\Omega(p) + C_r(p) \tag{4}$$

$$C_m(p) = K.I(p) \tag{5}$$

$$\mathrm{E}(p) = K.\Omega(p) \tag{6}$$

From the above equations the transfer function between armature voltage U and motor speed Ω can be written as:

$$\Omega(p) = \frac{K}{(f+Jp)(R+Lp)+K^2}U(p) - \frac{R+Lp}{(f+Jp)(R+Lp)+K^2}C_r(p) \tag{7}$$

The block diagram of the separately excited DC motor used in this study is shown in Figure 2.

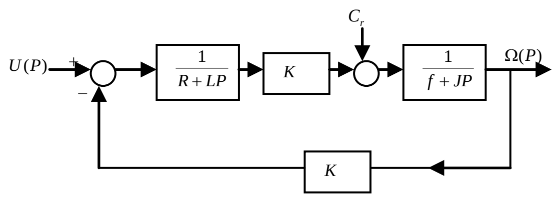

Fig. 2. The bloc diagram of the dc motor

3. Model identification of separately excited DC motor

System identification is the process of developing a mathematical model of a dynamic system based on sampled input and output data from the actual system. An advantage of system identification is evident if the process is changed or modified. System identification allows the real system to be altered without having to calculate the dynamical equations and model the parameters again [5].

The on-line identification of SISO process has been applied to identify separately excited DC motor. The armature voltage has been perturbed by pseudo random binary signal generated by the process computer.

The input data of a separately excited DC motor consist of the armature voltage, the output data is the speed of a DC motor.

With the obtained data, and using the MATLAB Identification Toolbox, the model identification of a separately excited DC motor was obtained using the prediction error method and an ARX model [6].

The identification tests were performed with a sampling time of 0.2 seconds. Figure 3 presents the structure that was implemented in Simulink and then used to obtain the identification data.

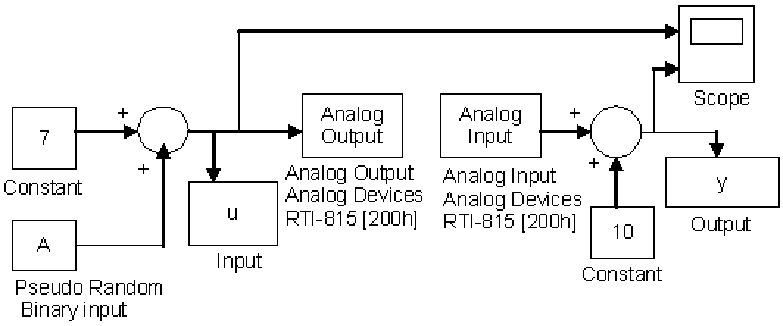

Fig. 3. Simulink Bloc Diagram used for identification

Figure 4 presents the motor output response for pseudo random binary input voltage signal. One tackles the process by a level of amplitude 7V until steady state was achieved, then a pseudo random binary input voltage signal which varies between -3 and 3V was applied.

The obtained model of a separately excited DC motor dynamics as follows:

$$A(z^{-1})y(t) = B(z^{-1})u(t-k) + C(z^{-1})e(t) \quad (8)$$

$$A(z^{-1}) = 1 - 1.099z^{-1} + 0.1778z^{-2}$$

$$B(z^{-1}) = 0.01754 + 0.01718z^{-1}$$

$$C(z^{-1}) = 1$$

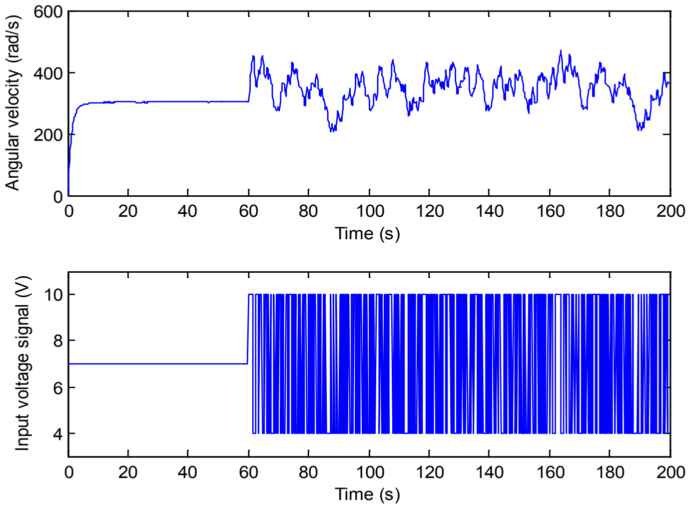

Fig. 3. DC motor output response for pseudo random binary input voltage signal

4. Control algorithm

When considering regulation about a particular operating point, even a non-linear plant generally admits a locally linearized model:

$$A(q^{-1})y(t) = B(q^{-1})u(t-1) + w(t) \qquad (9)$$

Where, A and B are polynomials in the backward shift operator q^{-1} :

$$A(q^{-1}) = 1 + a_1 q^{-1} + \ldots + a_{na} q^{-na}$$
$$B(q^{-1}) = b_0 + b_1 q^{-1} + \ldots + b_{nb} q^{-nb}$$

If the plant has a non-zeros dead-time the leading elements of the polynomial $B(q^{-1})$ are zero. In (9) u(t) is the control input , y(t) is the measured variable or output, and w(t) is a disturbance term.

In literature w(t) has been considered to be of moving average form:

$$w(t) = \frac{C(q^{-1})}{\Delta(q^{-1})}\xi(t) \qquad (10)$$

Where, $C(q^{-1}) = 1 + c_1 q^{-1} + \ldots + c_{nc} q^{-nc}$

In this equation $\xi(t)$ is uncorrelated random sequence, and combining With (9) we obtain the CARIMA model:

$$\Delta A(q^{-1})y(t) = B(q^{-1})\Delta u(t-1) + C(q^{-1})\xi(t) \qquad (11)$$

Where, Δ is the differencing operator $1-q^{-1}$ and q^{-1} is the backward shift operator such that: $q^{-1}y(t) = y(t-1)$ .For simplicity in the here $C(q^{-1})$ is chosen to be 1.

The objective of the GPC control is the output y(t) to follow some reference signal y*(t) taking into account the control effort. This can be expressed in the following cost function:

$$J(h_i,h_p,h_c,t)=\left\{\sum_{h_i}^{h_p}\left[y(t+j)-y^*(t+j)\right]^T R\left[y(t+j)-y^*(t+j)\right]+\sum_{h_i}^{h_c}\Delta u^T(t+j-1)Q\Delta u(t+j-1)\right\}$$

Where, h_p is the prediction horizon, h_i is the initial horizon, h_c is the control horizon, y*(t) is the output reference, R is the output weighting factor and Q is the control weighting factor.

The control objective is to compute at each time t, control inputs that minimize the quadratic criterion $J(h_i,h_p,h_c,t)$.

For this there are two cases:

Case 1: $h_c = h_p, h_i = 1$

Let us first build j-step ahead predictors with following Diophantine equation:

$$1 = E^j(q^{-1})A(q^{-1})\Delta(q^{-1}) + q^{-j}F^j(q^{-1}) \qquad j = 1\ldots h_p \quad (12)$$

Where,

$$E^j(q^{-1}) = 1 + e_1 q^{-1} + \ldots + e_{j-1}q^{-(j-1)}$$
$$F^j(q^{-1}) = f_0^j + f_1^j q^{-1} + \ldots + f_{na}^j q^{-na}$$

The polynomials $E^j(q^{-1})$ and $F^j(q^{-1})$ are uniquely defined by: $A(q^{-1})$, $\Delta(q^{-1})$ and j.

Using equations (9) and (12) we obtain:

$$y(t+j) = E^j(q^{-1})B(q^{-1})\Delta u(t+j-1) + F^j(q^{-1})y(t) + E^j(q^{-1})\xi(t+j) \quad (13)$$

The optimal predictor, given measured output data up to time t and any given u(t+i) for i>1, is clearly:

$$\hat{y}(t+j/t) = G^j(q^{-1})\Delta u(t+j-1) + F^j(q^{-1})y(t) \quad (14)$$

Where, $G^j(q^{-1}) = E^j(q^{-1})B(q^{-1})$

Defining, $G^j(q^{-1}) = g_0^j + g_1^j q^{-1} + \ldots + g_{j-1}^j q^{-(j-1)}$

Then the equations above can be written in the key vector form:

$$\hat{Y} = G\Delta U_t + Y_0 \quad (15)$$

Where, the vectors are all $h_p \times 1$:

$$\hat{Y}^T = \left[\hat{y}^T(t+1) \ldots\ldots\ldots\ldots \hat{y}^T(t+h_p) \right] \quad (16)$$

$$\Delta U_t^T = \left[\Delta U_t^T(t) \ldots\ldots\ldots\ldots \Delta U_t^T(t+h_p-1) \right] \quad (17)$$

$$Y_0^T = \left[y_0^T(t+1) \ldots\ldots\ldots\ldots y_0^T(t+h_p) \right] \quad (18)$$

Note that $G^j(q^{-1}) = B(q^{-1})\left[1 - q^{-j}F^j(q^{-1})\right] / A(q^{-1})\Delta$ so that one way of computing G^j is simply to consider the Z-transform of the plant's step-response and to take the first j terms and therefore $g_i^j = g_j$ for j=0,1,2,…< i independent of the particular G polynomial [2].

The matrix G is then lower-triangular of dimension $h_p \times h_p$:

$$G = \begin{bmatrix} g_0 & 0 & \cdots & \cdots & 0 \\ g_1 & g_0 & \cdots & \cdots & 0 \\ . & .. & \cdots & \cdots & . \\ \vdots & & & & \vdots \\ g_{h_p-1} & g_{h_p-2} & \cdots & \cdots & g_0 \end{bmatrix} \quad (19)$$

Note that if the plant dead time d > 1 the first d-1 rows of the G will be null, but if instead h_i is assumed to be equal to d the leading element is non-zero [2].

From the definitions above of the vectors and with:

$$Y^{*T} = \left[y^{*T}(t+1) \ldots\ldots\ldots\ldots y^{*T}(t+h_p) \right] \quad (20)$$

The expectation of the cost-function can be written as follows:

$$J(h_i, h_p, h_c, t) = (G\Delta U_t + Y_0 - Y^*)^T R(G\Delta U_t + Y_0 - Y^*) + \Delta U_t Q \Delta U_t^T \quad (21)$$

The solution, ΔU_t minimizing the criterion can be explicitly found, using:

$$\frac{\partial J}{\partial \Delta U_t} = 0 \tag{22}$$

it follows that:

$$\Delta U_t^* = (G^T G + Q)^{-1} G^T R(Y_0 - Y^*) \tag{23}$$

Note that the first element of ΔU_t^* is $\Delta u(t)$ so that the current control u(t) is given by:

$$u(t) = u(t-1) + (G^T G + Q)^{-1} G^T R(Y_0 - Y^*) \tag{24}$$

Case 2: $h_c < h_p, h_i = 1$

It is possible to reduce computational burden by imposing a constant control input vector after a fixed horizon h_c $(\Delta u(t + j - 1) = 0 \ \text{ for } j > h_c)$

In this case the vector ΔU_t and the matrix G become:

$$\Delta U_t^T = \left[\Delta U_t^T(t) \ldots\ldots\ldots \Delta U_t^T(t + h_c - 1)\right] \tag{26}$$

$$G = \begin{bmatrix} g_0 & 0 & \cdots & \cdots & 0 \\ g_1 & g_0 & \cdots & \cdots & 0 \\ . & .. & \cdots & \cdots & g_0 \\ \vdots & & & & \vdots \\ g_{h_p-1} & g_{h_p-2} & \cdots & \cdots & g_{h_p-h_c} \end{bmatrix} \tag{27}$$

5. Adaptive control algorithm

The adaptive controller which is proposed here is indirect controller. To estimate the unknown system parameters $\theta = (a_1, \ldots, a_{na}, b_0, \ldots, b_{nb})^T$ the Recursive Least Squares (RLS) algorithm is applied. Next the current system parameter estimates $\hat{\theta}$ are used for tuning of the Generalized Predictive Controller. Thus, the obtained Adaptive Generalized Predictive Controller generates the current control signal.

The following (RLS) algorithm has been used:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \frac{\varepsilon(t)\Delta\Phi(t-1)F(t-1)}{1 + \Delta\Phi^T(t-1)F(t-1)\Delta\Phi(t-1)} \tag{28}$$

$$\varepsilon(t) = \Delta y(t-1) - \theta(t-1)\Delta\Phi(t-1) \quad (29)$$

$$F(t) = \frac{1}{\lambda_1(t)}\left[F(t-1) - \frac{\Delta\Phi(t-1)\Delta\Phi^T(t-1)F(t-1)}{\frac{\lambda_1(t)}{\lambda_2(t)} + \Delta\Phi^T(t-1)F(t-1)\Delta\Phi(t-1)}\right] \quad (30)$$

Where,

$$\hat{\theta}(t) = \left[\hat{a}_1, \ldots, \hat{a}_{na}, \hat{b}_0, \ldots, \hat{b}_{nb}\right]^T$$

$$\Phi(t) = \left[y^T(t-1), \ldots, y^T(t-na), u^T(t-1), \ldots, u^T(t-n_b)\right]^T$$

$\varepsilon(t)$ is the estimation error, $\Phi(t)$ is the vector of data input-output, F(t) is the adaptation gain, $\lambda_1(t)$ and $\lambda_2(t)$ represents forgotten factors.

6. Simulation and discussion

In order to illustrate the behavior of the above presented Adaptive Generalized Predictive Control algorithm, the simulation results of a separately excited DC motor model obtained by using on-line identification technique [6], are given. The model is chosen as follows:

$$y(t) - 1.099y(t-1) + 0.1778\,y(t-2) = q^{-1}(0.01754u(t-1) + 0.01718\,u(t-2))$$

Several experiments have been carried out to determine a suitable control model order an appropriate sample time for control. A second order model (n_a=2, n_b=1 and delay=1) sampled at 0.2 second gave a reasonable description of a separately excited DC motor dynamics.

The initial covariance matrix $F(0) = 10^{\wedge 6}$ and the polynomial $C(q^{-1})$ is chosen as: $C(q^{-1}) = 1$.

The control objective design parameters are: $h_p = 7$, $h_c = 2$, $h_i = delay$, $Q = 0.98$, and R=1.

The objective of the separately excited DC motor control is to track a reference. The prediction controller parameters (h_p, h_c, h_i, Q and R) are chosen in order to get an acceptable tracking.

First the non-disturbed separately excited DC motor system is controlled by GPC control and Adaptive Generalized Predictive Controller to tack the set point. The tracking response is shown in figures 4 and 5, where we seen that the tracking performance is successfully achieved.

Then, the separately excited DC motor output is affected by small random disturbance ($\sigma^2 = 0.1$) as show in figures 7 and 8. It can be seen that the system response follows the reference and the effect of disturbance is well rejected.

The behavior of the model's parameters in case of adaptive predictive control is shown in figures 6 and 9.

Case 1: Simulation results in noise absence conditions:

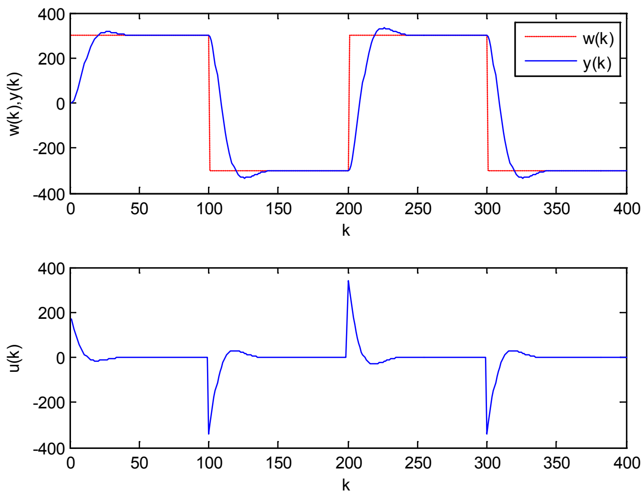

Fig. 4. Plant output and control input in noise absence conditions: GPC control

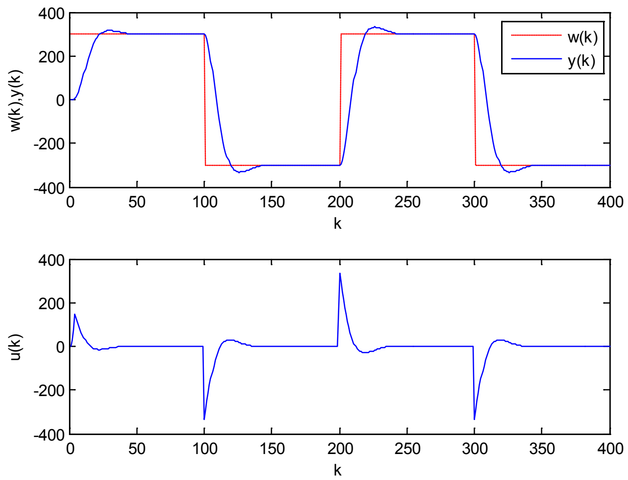

Fig. 5. Plant output and control input in noise absence conditions: Adaptive predictive control

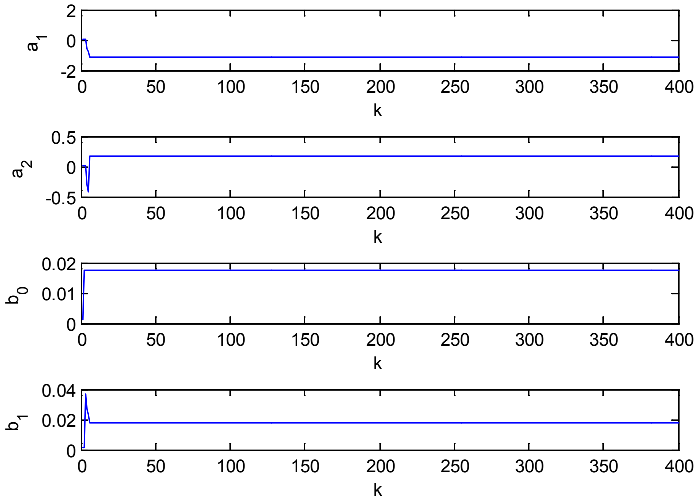

Fig. 6. Tuned parameters in noise absence conditions

Case 2: Simulation results in noise presence conditions:

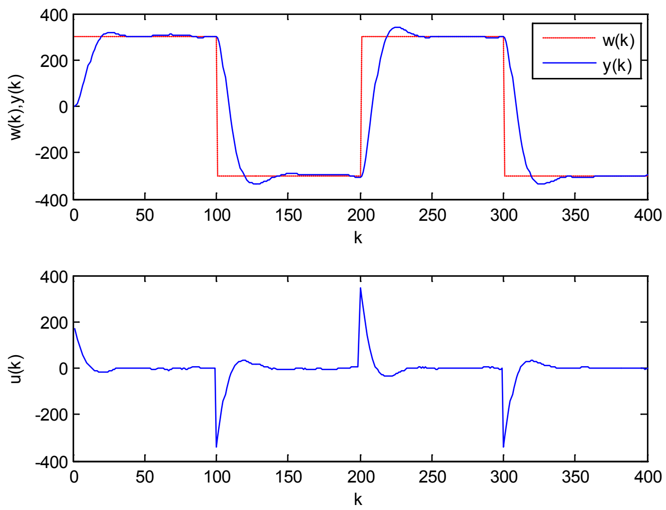

Fig. 7. Plant output and control input in noise case: GPC control

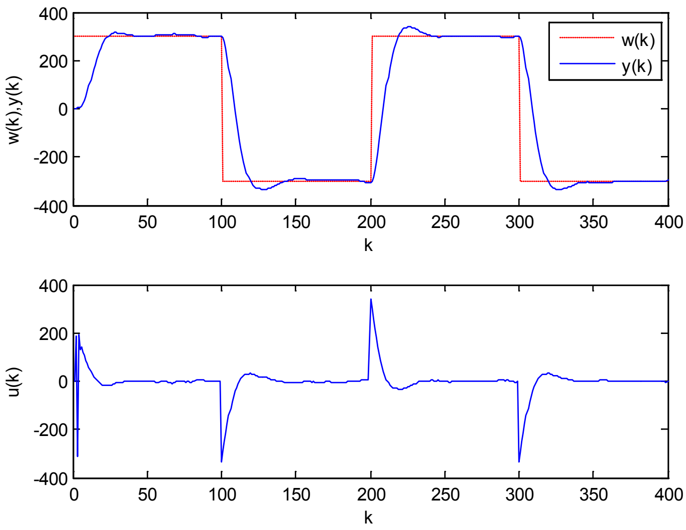

Fig. 8. Plant output and control input in noise case: Adaptive predictive control

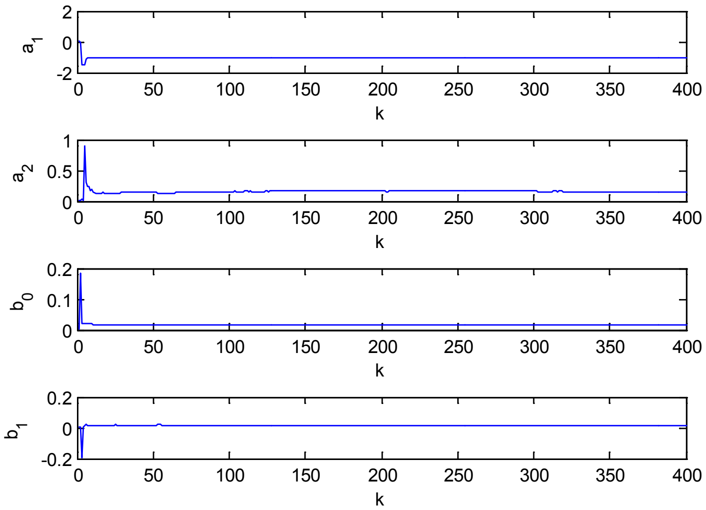

Fig. 9. Tuned parameters in noise case

7. Conclusion

In this paper, an Adaptive Generalized Predictive Control strategy is applied to a separately excited DC motor. The prediction model is designed using the Diophantine equation solution. Result show that the separately excited DC motor under Adaptive Generalized Predictive Control has a good control output tracking performance and the disturbance is well rejected.

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