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DSP-Based Adaptive and Self-Tuning Control of an Adjustable Speed DC Drive System

VASILE HORGA [1] ALEXANDRU ONEA [2] MIHAI ALBU [1]
[1]Department of Electric Drives
[2] Department of Automatic Control and Industrial Informatics
"Gh. Asachi" Technical University of Iaşi
Bd. Mangeron. 53A, 6600 Iaşi
ROMANIA

Abstract: - The paper presents a solution of self-tuning control applied to a chopper-driven motor system. On that purpose the mathematical model of the plant is firstly delivered. It was preferred an on-line system parameters estimation based on continuous time model. The adaptive and self-tuning algorithms were implemented on a floating-point DSP.

Key-Words: - DC motor drive, self-tuning, adaptive control, DSP, identification, discrete time model, continuous time model, Poisson moment functional

1 Introduction

Many adjustable speed drive applications require medium or high bandwidth torque control in order to obtain adequate control performances. It means that a drive system will be able to perform the desired motion control operation if it can operate as a controllable source of torque.

Without torque control, the dynamic performance of a drive is at best slow and oscillatory, and in the worst case unstable. High performance control of electric drives requires the accurate models of the motor and mechanical load.

Self-commissioning greatly improves the drive tuning and performance, but its effects are consistent only if the motor remains inside the tuning range. Some system damages can be unpredictable and ordinary closed-loop systems may not respond properly when the system transfer function varies. The adaptive control helps to deliver both stability and good response.

The self-tuning regulators contain an inner control loop and an outer adaptation loop. The inner control loop acts on the plant in the conventional way. The outer loop adjusts the inner loop controller parameters. The outer loop consists in a recursive parameter estimator combined with a control design algorithm. A self-tuning regulator assumes a linear model for the controlled process. The estimated values of the plant parameters are used in a control law design algorithm. This one sends the new controller coefficients to the controller of the inner loop.

The paper describes a DSP-based on-line adaptive and self-tuning control method for an adjustable speed drive system. This system consists in a chopper and a DC motor. The main objective of this paper is to present an automated methodology for the estimation of electrical and mechanical parameters of the drive system that are used to tune the controllers of the ordinary control loops.

2 Mathematical Model of Adjustable Speed Drive of a Chopper-Driven DC Motor

A separately excited DC motor drive was used. Excitation flux is assumed to be constant and equal to rated value all time. Then the motor can be represented as a system of two first order differential equations:

$$\begin{aligned} L_a \frac{di_a}{dt} &= v_a - R_a i_a - K\Omega \\ J\frac{d\Omega}{dt} &= Ki_a - t_L - D\Omega \end{aligned} \qquad (1)$$

where: L_a, R_a-inductance/resistance of the armature circuit, K-counter electromotive force and torque constant, J-inertia of the system, D-viscous friction coefficient, i_a-armature circuit current, v_a-armature circuit voltage, Ω-motor speed, t_L-load torque.

The conventional control structure of a separately excited DC motor is the classical cascade control. Conventional constant parameter PI controllers are used for armature current and speed control. The PI controller for current is designed using modular optimum criterion and the PI controller for speed is designed using improved symmetrical optimum criterion [1]. The output of the speed controller is limited and an anti-windup system is included to reduce the current overshoot that may result due to integrator saturation.

From the modular optimum criterion the parameters values of the current controller are:

$$K_{Ri} = \frac{T_{el} R_a}{2 K_a K_{Ti} T_{\Sigma i}} = C_1 L_a; \quad T_{el} = \frac{L_a}{R_a}; \qquad T_{ii} = T_{el} \qquad T_{\Sigma i} = T_\mu + T_{fi} \tag{2}$$

where: T_{el}-electrical time constant, T_μ-dead-time caused by the chopper, T_{fi}-time constant of the filter inserted for the measured current, K_a-gain of the chopper, K_{Ti}-constant of the current transducer.

The symmetrical optimum criterion gives the following parameters for the speed controller:

$$K_{R\Omega} = \frac{J K_{Ti}}{2 K K_{T\Omega} T_{\Sigma\Omega}} = C_2 \frac{J}{K}; \qquad T_{i\Omega} = 4 T_{\Sigma\Omega} \qquad T_{\Sigma\Omega} = 2 T_{\Sigma i} + T_{fi} + T_{f\Omega} \tag{3}$$

where $K_{T\Omega}$ is the constant of the speed transducer and $T_{f\Omega}$-time constant of the measured speed filter.

With an adequate sampling period, the continuous control laws of the conventional structure are approximated with discrete control laws and implemented on a floating-point DSP system.

3. On-line System Parameters Estimation Based on Discrete Model

As result of the fast development in automation technology the demand for drives increases. An important problem in drive systems is controller tuning prior to system operation. Drives controller tuning is needed to ensure that the drive system will meet the system performance requirements. Drive commissioning is the tuning of system parameters before it operates. During this process, different test are applied to calibrate the drive controller.

Self-commissioning is the automation of the commissioning process. One of the benefits of self-commissioning is that it facilitates system installation and ensures proper drive tuning before the system is fully operational. That means significant improvements in reliability of drive system by increasing the intelligence of the control systems.

Parameter estimation is necessary for proper tuning of the controllers. The physical parameters of the system should be accurately estimated. The Recursive Least Squares (RLS) algorithm allows computation of the unknown coefficients of a set of linear difference equations.

If the difference equation describing the process

$$y(k) + a_1 y(k-1) + .. + a_n y(k-n) = = b_0 u(k-1) + .. b_m u(k-m-1) \tag{4}$$

is put into linear regression form as

$$y(k) = \varphi^T(k)\theta(k)$$

$$\varphi(k) = [-y(k-1) .... - y(k-n)\ u(k-1) .....u(k-m-1)]^T$$

$$\theta = [a_1\ a_2 .... a_n\ b_0\ \ b_1 ....b_m]^T \tag{5}$$

then the equations to be solved every sampling interval are:

$$P(k) = P(k-1)\left[I - \frac{\varphi(k)\varphi^T(k)P(k-1)}{1 + \varphi^T(k)P(k-1)\varphi(k)}\right] \tag{6}$$

$$\xi(k) = y(k) - \varphi^T(k)\hat{\theta}(k-1) \tag{7}$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\varphi(k)\xi(k) \tag{8}$$

With RLS being an algorithm for the recursive solution of a system of linear equations, the process to be identified has to be transformed into a model of difference equation.

Time series analysis, ARMA (z-transform) estimation using least squared error coefficient fitting, has been used for decade to numerically identify system model in the discrete time domain [2]. With input and output signals sampled at equal time intervals and a linear model structure relating the two sets of signals, coefficients of the discrete model can be found using this technique. From these coefficients, the physical parameters of the system can be calculated in order to update the parameters of the used controllers. Unfortunately, little attention has been paid to the accuracy of the estimated physical parameters resulting from this identification procedure.

In the case of discrete models there are a number of difficulties related to the used discretzation method such as possible multiple local minima. Furthermore, a precise estimation of the discrete model parameters does not guarantee that the correct continuous model parameters will be recovered [3]. The sampling time for these identification technique has to be carefully chosen. Operating with too large sampling intervals dominant poles or zeros may be neglected or the resonant frequency may not be sensed.

It is widely known that the sample rate must be fast enough to avoid aliasing. A common misconception is that the best identification results can be obtained by sampling as fast as the hardware will allow. Such high sample rates actually cause errors and are unsuitable. Choosing a sampling interval which is too small numerical problems may arise.

In the continuous time domain a stable root can fall anywhere in the left half of the s-plane. This infinite region corresponds to a unit circle in the z-plane. Because an infinite area is condensed into the finite and small area of a unit circle, there are regions of the z-plane where the discrete time root is insensitive to the continuous time root [2],[4]. These regions of the discrete time domain should be avoided. Given fixed dynamics, the only way to avoid these regions is with a proper selection of the sample rate.

On the other hand, in order to guarantee fast reaction of the controllers, especially in case of disturbances, the goal is to choose the sampling time of the controllers to be as small as possible, thus gaining nearly continuous performance. Therefore with the sampling time for the controller different from the one for estimation, the plant model has to be transformed at least from one sampling time to another. Besides the z-transform of the plant may have non-minimum phase zeros, which have no equivalent in the continuous s-plane, and which may cause problems while computing an appropriate controller.

All these emphasized problems may be avoided if the recursive estimator is based on continuous models of the plant.

4 On-line System Parameters Estimation based on Continuous Time Model

Parameter estimation of continuous time systems is not a new subject. In the old days, when computers were not around, the continuous time perspective was dominating. Research on the subject of continuous estimation has not been intense until lately, but has instead been slowly going on since the nineteen fifties [5].

A continuous time model is more appropriate than a discrete one. The estimation methods on continuous time model offer the following advantages:

- an easier use of the obtained model by the supervision level in adaptive systems;
- the change of the sample rate of the control system, which is usually different from the sampling rate used for the estimation;
- the possibility to embed a priori knowledge about partially known process in terms of poles, zeros or physical quantities.

Consider the task of estimating an ARMA system modeled by the linear differential equation:

$$\sum_{i=0}^{n} a_i \frac{d^i}{dt^i} y(t) = \sum_{j=0}^{m} b_j \frac{d^j}{dt^j} u(t);\ a_0 = 1, m < n \qquad (9)$$

One way of determining the unknown coefficients a_i's and b_j 's is to observe the input u(t) and the output y(t), create the derivative terms artificially, substitute them into regression equation (10) that can be used by RLS estimator.

$$y(t) = \varphi^T(t)\theta \qquad (10)$$

$$\varphi(t) = \left[-\frac{dy(t)}{dt} - \frac{d^2y(t)}{dt^2} \ldots - \frac{d^ny(t)}{dt^n}\, u(t)\, \frac{du(t)}{dt} .. \frac{d^mu(t)}{dt^m} \right]^T \qquad (11)$$

$$\theta = [\, a_1\ a_2\ \ldots .\, a_n\ b_0\ \ b_1 \ldots .\, b_m\,]^T \qquad (12)$$

The drawback of this fairly straightforward approach is the difficulty of obtaining the derivatives of the input and the output which in practice inevitably contain noise. Algorithms involving direct generation of the time derivatives of signals either physically or by computing remain satisfactory for the high signal to noise ratio.

The fact that differentiation is an intrinsically noise accentuating operation motivated many researchers in the early nineteen sixties to devise methods that are noise resistant. The solution is to perform Linear Dynamical Operation (LDO) in both terms of equation (9) and transform the differential equation for the continuous time system into a system of algebraic equations.

The PMF can be interpreted as a technical application of the Shinbrot modulating function method [6]. The principle of the PMF consists of converting a continuous time signal z(t) over the time interval $[0,t_0]$ into a real number Z(t), called moment of the signal z(t).

Let's define the Gamma kernel as [7]:

$$g_n(\lambda, t) = \frac{\lambda^n t^{n-1}}{(n-1)!} e^{-\lambda t};\quad \lambda > 0, t \ge 0, \quad \lambda \in R \qquad (13)$$

The Gamma kernel refers to the implementation of a generalized delay operator. The Laplace transform of the kernels is given as:

$$G_n(s) = \left(\frac{\lambda}{s+\lambda} \right)^n = G^n(s) \qquad (14)$$

where

$$G(s) = L\{g_1(\lambda, t)\} = \frac{\lambda}{s+\lambda} \qquad (15)$$

Equation (14) suggests a practical implementation for the kernels, in the form of a cascade of identical first order low pass filters. This structure is called the Gamma filter. The impulse response of the filter from the input to the k^{th} tap is given by $g_k(\lambda, t)$. The time scale λ is responsible for setting the position of the pole s=-λ .

The convolution integrals can be viewed as the outputs of various stages of a set of filter chains. The convolution theorem allows to define the LDO of k degree the operation performed by a k+1st order Gamma filter.

$$Z_k^0(t) \overset{not}{=} M_k\{z(t)\}_{t_0} = \int_0^{t_0} \frac{\lambda^{k+1}}{k!}(t_0 - t)^k e^{-\lambda(t_0 - t)} z(t)dt \quad (16)$$

This is known as PMF of k degree. Generalizing, if at the input of k+1st order Gamma filter is applied a signal, signifying the n-order derivative of z(t) one obtain:

$$Z_k^n(t) \overset{not}{=} M_k\left\{\frac{d^n z(t)}{dt^n}\right\}_{t_0} = \int_0^{t_0} \frac{\lambda^{k+1}}{k!}(t_0 - t)^k e^{-\lambda(t_0 - t)} \frac{d^n z(t)}{dt^n} dt \quad (17)$$

It can be shown that the j-order PMF of the z(t) signal has the property [8]:

$$Z_k^j(t) = \lambda Z_{k-1}^{j-1}(t) - \lambda Z_k^{j-1} - g_{n+1}(\lambda, t_0)\frac{d^{j-1}z(0)}{dt^{j-1}} \quad (18)$$

The last term in (18) take into account the combined effects of initial condition and in on-line applications can be ignored because the filters are stable and causal.

Applying the n-order PMF to the equation (9) yields:

$$y_n^0(t) = \varphi^{*T}(t)\theta \quad (19)$$

$$\varphi^*(t) = \left[-Y_n^1(t) - Y_n^2(t) \ldots - Y_n^n(t)\ U_n^0(t)\ U_n^1(t) .. U_n^m(t)\right]^T \quad (20)$$

$$\theta = [\, a_1\ a_2\ \ldots .\ a_n\ b_0\ b_1\ \ldots . b_m\,]^T \quad (21)$$

This is an algebraic equation linear in parameters obtained from differential equation (9) assuming that the input-output signals of the system are measured.

5 Self-tuning and Adaptive Control of the DC Drive System

The DC motor is characterized by the transfer functions:

$$\frac{I_a(s)}{U_a(s)} = \frac{\frac{1}{L_a}s + \frac{D}{L_a J}}{s^2 + \left(\frac{R_a}{L_a} + \frac{D}{J}\right)s + \frac{R_a}{L_a}\frac{D}{J} + \frac{1}{L_a}\frac{K^2}{J}} = \frac{b_1 s + b_0}{s^2 + a_1 s + a_0} \quad (22)$$

$$\frac{\Omega(s)}{I_a(s)} = \frac{\frac{K}{J}}{s + \frac{D}{J}} = \frac{b_0^*}{s + a_0^*} \quad (23)$$

where

$$b_1 = \frac{1}{L_a};\ b_0 = \frac{D}{L_a J};\ a_1 = \left(\frac{R_a}{L_a} + \frac{D}{J}\right);$$

$$a_0 = \frac{R_a}{L_a}\frac{D}{J} + \frac{1}{L_a}\frac{K^2}{J};\ b_0^* = \frac{K}{J};\ a_0^* = \frac{D}{J} \quad (24)$$

The motor model is completely specified if the parameters R_a, L_a, K, J and D are given. These five parameters can be calculatated if the coefficients of the transfer functions are known.

$$L_a = \frac{1}{b_1};\ T_{el} = \frac{L_a}{R_a} = \frac{1}{a_1 - a_0^*};\ R_a = \frac{L_a}{T_e} = \frac{a_1 - a_0^*}{b_1}$$

$$K = \frac{\left(a_0 - a_0^*\left(a_1 - a_0^*\right)\right)}{b_1 b_0^*};\ J = \frac{K}{b_0^*} = \frac{\left(a_0 - a_0^*\left(a_1 - a_0^*\right)\right)}{b_1 b_0^{*2}};$$

$$D = J a_0^* = \frac{a_0^*\left(a_0 - a_0^*\left(a_1 - a_0^*\right)\right)}{b_1 b_0^{*2}} \quad (25)$$

The regression equations associated with the transfer functions (22) and (23) are

$$\frac{d^2 i_a(t)}{dt^2} = -a_1\frac{di_a(t)}{dt} - a_0 i_a(t) + b_1\frac{du_a(t)}{dt} + b_0 u_a(t) = \left[-\frac{di_a(t)}{dt}\ \ -i_a(t)\ \ \frac{du_a(t)}{dt}\ \ u_a(t)\right][a_1\ \ a_0\ \ b_1\ \ b_0]^T \quad (26)$$

and

$$\frac{d\Omega(t)}{dt} = -a_0^*\Omega(t) + b_0^* i_a(t) = \left[-\Omega(t)\ \ i_a(t)\right]\left[a_0^*\ \ b_0^*\right]^T \quad (27)$$

According to PMF these two equations can be substituted with

$$I_{a2}^2(t) = \left[-I_{a2}^1(t)\ \ -I_{a2}^0(t)\ \ U_{a2}^1(t)\ \ U_{a2}^0(t)\right][a_1\ \ a_0\ \ b_1\ \ b_0]^T \quad (28)$$

$$\Omega_2^1(t) = \left[-\Omega_2^0(t)\ \ i_2^0(t)\right]\left[a_0^*\ \ b_0^*\right]^T \quad (29)$$

The structure of the on-line estimation modules for physical motor parameters is presented in Fig.1.

When the physical parameters of the motor are obtained they are used for the tuning of current and speed controllers as in Fig.2. In the adaptive control drive system, the numerical device will compute the new values of the continuous parametrs of the PI controllers and, after that, it will compute the new parametrers of the dicrete control laws using also the value assigned for the sampling period T.

6 Experimental results

Because of the amount of calculations involved, a floating point DSP system is used [9]. The dc motor nominal values are: P_n=1.7Kw, U_n=110V, I_a=20A, Ω_n=1500rpm. The gain of the chopper is K_a=125.

The recursive estimator must be correctly initialized ($P(0),\ \hat{\theta}(0)$). Even with correct initial values the estimations are not reliable during the transient time of the estimator. These initial estimations can cause dangerous commands which will determine actions of the chopper protections if they are used immediately by the adjusting parameters block. Two solutions were found for this problem: the adaptation loop will be closed after the transient time of the estimator and the drive system is controlled during this time with a rough tuned control loop, or for the transient time of the estimator the chopper is feed with a test signal that will allow a correct estimation of the physical parameters and after that the adaptation loop is connected. In the experiments the second solution was adopted.

The physical parameters estimation is fully automated. This means that the electrical drive system possesses the self-tuning property.

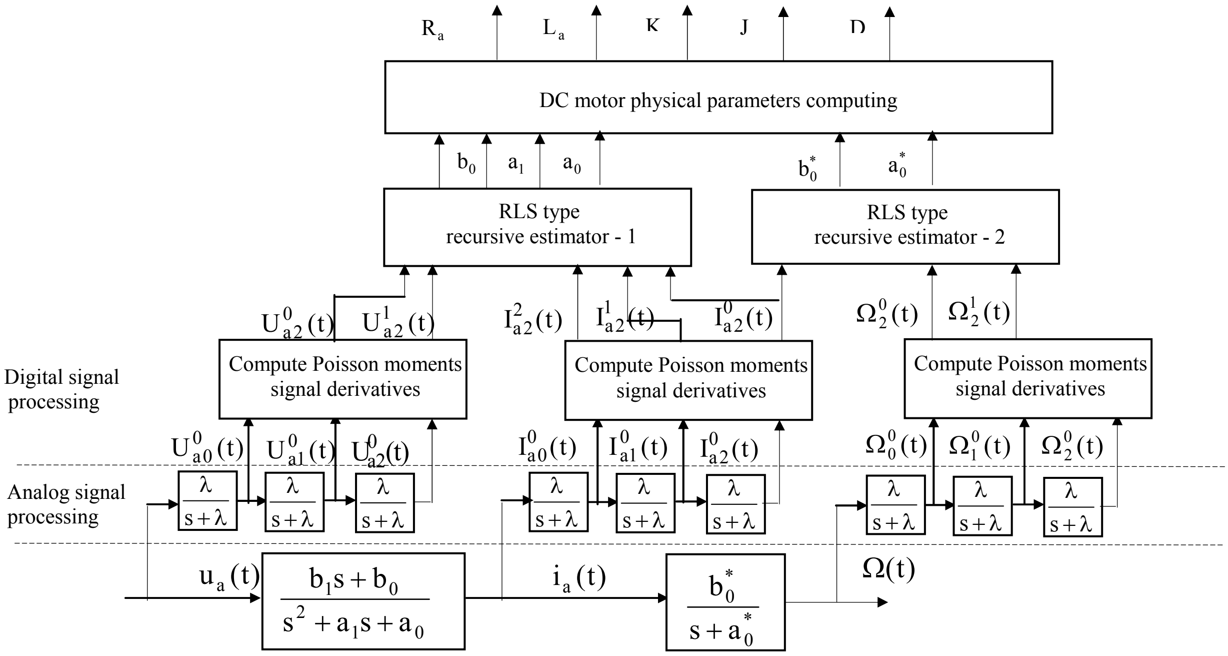

Fig.1. Structure modules for on-line estimation of physical DC motor parameters

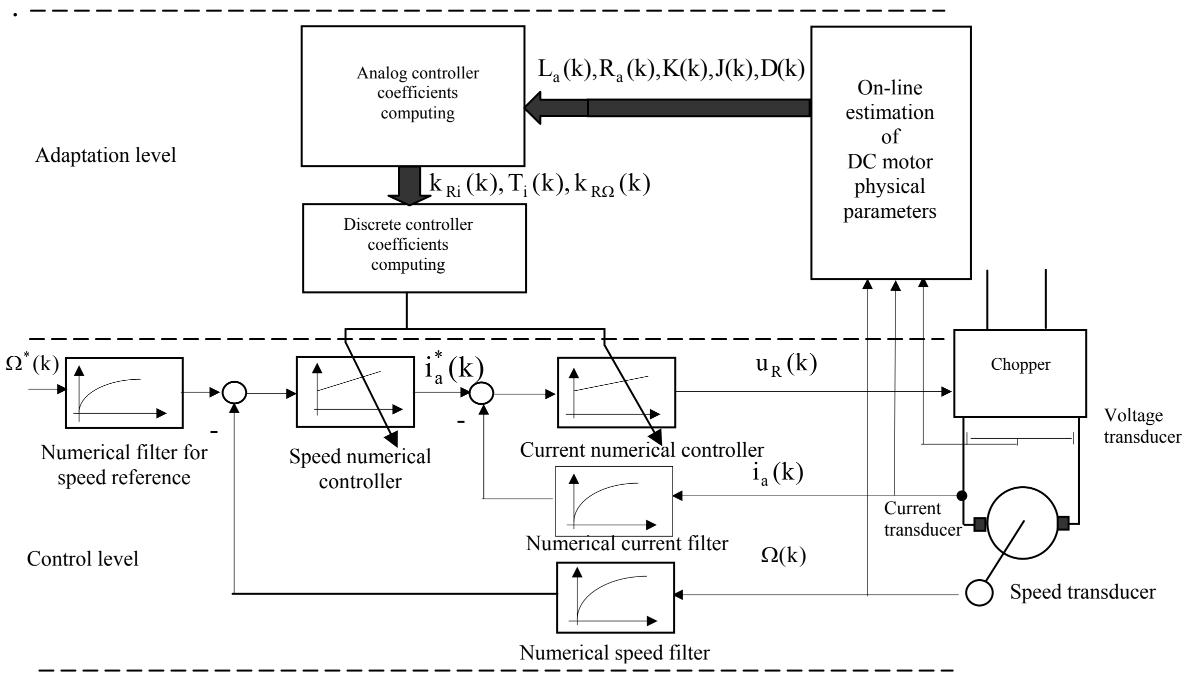

Fig.2. Adaptive structure of an electrical drive system with DC motor

Once the controllers parameters tuned, the recursive estimator can be inhibited after 2.3 seconds. Because it remains activated even in the operating regime, it is sensitive to the parameters variations and allows a continuous adaptation.

When the elements of the diagonal of covariance matrix P(k) have shrunk to very small values the estimator becomes disable. To be set enable again the covariance matrix P(k) must be initialized periodically.

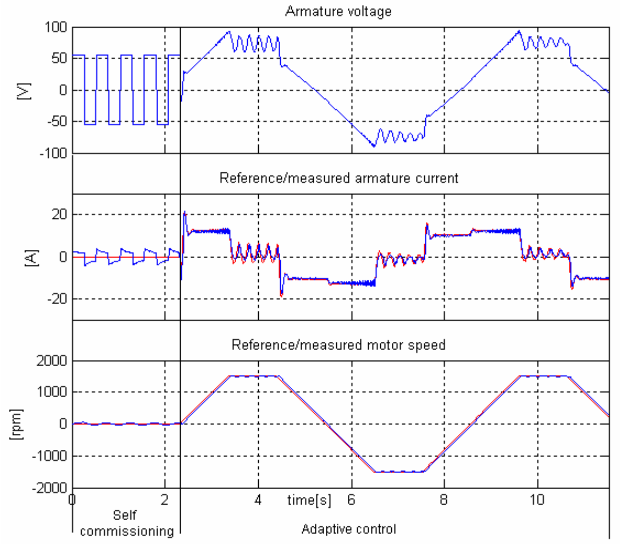

Fig.3. Electrical and mechanical signals of DC drive

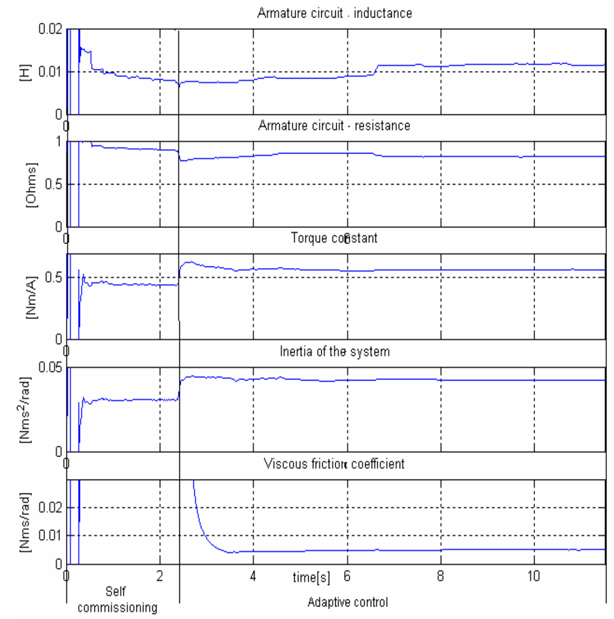

Fig.4. Estimated physical parameters of the motor

The experimental results for the self-commissioning interval and for the normal operating interval, when the system has a trapezoidal reference signal, are presented in Fig.3 and Fig.4. The conventional control loops and the adaptation loop are both executed with 1.54 milliseconds sampling period. In order to avoid additional analog circuitry, the analogue Gamma filters were replaced with digital filter algorithms.

The experimental results emphasis a correct estimation of the motor physical parameters, a good parameters stability, and, consequently, good control performances.

7 Conclusion

The paper presents a solution for practical implementation of an adaptive and self-tuning DC drive system. There are presented the inconveniencies which may arise when the adaptation loop uses an estimator based on a discrete model of the process. A robust estimation technique of the system physical parameters is obtained if it is used the continuous model of the process correlated with the Poisson moment functional. The experimental results show the feasibility of the proposed adaptive control method.

References:

[1]Nandam P., Sen P., Analog and Digital Control of DC Drives Using Proportional-Integral and Integral-Proportional Control Techniques, *IEEE Trans on Ind. Electronics*, Vol. IE-34, No.2, 1987, pp.227-233.

[2] Borgard Diane, Olsson G., Lorenz R., Accuracy Issues for Parameter Estimation of Field Oriented Induction Machine Drives, *IEEE Trans on Ind. Applications*, Vol. 31, No.4, 1995, pp.795-801.

[3] de Oliveira P., Peixoto Z., Parameter Estimation of an Induction Machine Using a Continuous Time Model, *IEEE Int. Symposium on Ind. Electronics*, Aachen, Germany, 1998, pp.292-296.

[4] Brickwedde A., On-Line and Selftuning Control for Complex Electrical Drive Systems, *European Power Conference*, Aachen, Germany, 1989, pp.1087-1095.

[5] Gillberg J., *Methods for Frequency Domain Estimation of Continuous Time Models*, University of Linköping, 2004.

[6] Shinbrot M., Field M., On the Analysing of Linear and Nonlinear Systems, *Trans ASME*, 1957, pp.547-552.

[7] Celebi S., *Representation of Locally Stationary Signals Using Lowpass Moments*, University of Florida, 1995.

[8] Horga V., Onea A., Graur I., Boţan C., On-Line Parameter Estimation of Induction Motor Based on Continuous Time Model, *Proc of the IASTED Int. Conference Control and Applications*, Cancun, Mexico, 2002, pp.214-219.

[9] Onea A., Horga V., Boţan C., Digital Motion Control Development Shell, *Proc. of the WSEAS Int. Conference Information, Simulation and Manufacturing Systems*, Cancun, Mexico, 2002, pp. 81-92.