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CONSIDERATION REGARDING IDENTIFICATION OF DYNAMIC PROCESS PARAMETERS

V. BAHRIN S. ARĂDOAEI[1]

Abstract: *In this paper are approached the issues regarding identifying of dynamic processes parameters of electric drive system. It is specified features of adaptive controllers. An analysis of least squares methods are used to estimate parameters of dynamic processes.*

Key words: *process parameters, controller, optimization.*

1. Introduction

The parameters of the automatic adaptive controller are influenced by changes in process (electric drive) and adjusted online [3]. To facilitate the analysis of convergence and stability properties of the system are considers that unknown parameters of the process are constant. After the identification process, the controller parameter values can be determined by a design method. Although, initially, the process is unknown, adaptive controller parameters will tend to these values; controller ensures the required performance and closed loop system is called self-tuning controller [2].

Self-tuning controller, Figure 1 contains a classical control loop, which has on the direct route of controlled process a controller. Controller parameter adjustment is performed by the feedback process inputs and outputs [1].

The unknown parameters of the controller can be estimated on-line through a recursive method: recursive least squares methods, expanded and generalized, stochastic approximation, instrumental variable method or maxim likelihood method. The block that performs the calculation of parameters, provide online solution for design problem of system whose parameters are unknown (underlying control problem). The controller properties can be modified by simultaneous application of an estimation methods and design method (minimum variance, linear quadratic, poles allocation or tracking model).

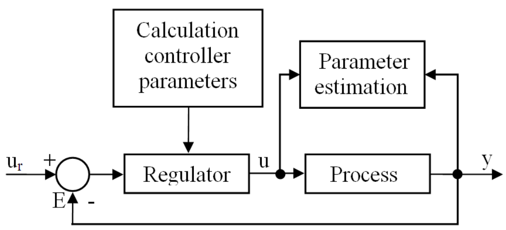

Fig. 1. *Self-tuning controller scheme*

The parameters of the transfer function corresponding to the process and perturbations are estimated through indirect adaptive control algorithm [8].

The controller parameters can be

[1] Dept. Electrical Engineering, *Gheorghe Asachi* Technical University of Iasi.

estimated directly by the model parameterization of controller parameters. Self-tuning controller can be applied to continuous or hybrid discrete systems [4].

2. Methods

By identifying (experimental determination) dynamic processes yielded signals that lead to the establishment of mathematical models that can determine the system behaviour [9]. The signals can be processed after each sampling time (real-time processing), or initially stored (batch-processing). Real time identification leads to good results in controlling adaptive systems and methods of estimation is performed by recursive process parameters.

Parametric and nonparametric models of processes can be used to design controllers. To establish parametric models resort to a finite number of parameters and methods can be applied to design high performance controller.

2.1. Non-recursive least squares method

It is considered a dynamic process [5] where is measured the signal $y(k)$ and $u(k)$ to the time kT, and the process parameters are estimated by the time of $(k–1)T$.

Under these assumptions, the resulting expression error is:

$$\begin{aligned} e(k) &= y(k)+a_1^*(k-1)y(k-1)+\dots \\ & a_m^*(k-1)y(k-m)-b_1^*(k-1)u(k-d+1)-\dots \\ & -b_m^*(k-1)u(k-d-m), \end{aligned} \tag{1}$$

where it is found the error caused by the noise that affects the output and error estimated parameters.

Prediction one step forward at the time $k–1$ is:

$$\begin{aligned} y^*(k-1) &= -a_1^*(k-1)y(k-1)-\dots \\ & a_m^*(k-1)y(k-m)-b_1^*(k-1)u(k-d+1)+\dots \\ & +b_m^*(k-1)u(k-d+1)=\Psi^T(k)\Theta^*(k-1), \end{aligned} \tag{2}$$

where:

$$\begin{aligned} \Psi^T(k) &= [-y(k-1)-\dots \\ & -y(k-m)u(k-d+1)..u(k-d-m)], \end{aligned} \tag{3}$$

is the vector of data, and $\Theta^*(k)=[a_1^*\dots\dots a_m^* b_1^*\dots\dots b_m^*]$ is the vector of parameters.

The output error is given by:

$$e(k) = y(k) - y^*(k-1) \tag{4}$$

when both inputs and outputs are measured in the range $k = [1, m + d + N]$, resulting $N + 1$ equation as:

$$y(k) = \Psi^T(k)\Theta^*(k-1) + e(k), \tag{5}$$

which, can be expressed as vector.

By imposing the condition of minimum for criterion function,

$$\begin{aligned} V &= e^T(m+d+N)e(m+d+N) \\ &= \sum_{k=m+d}^{m+d+N} e^2(k), \end{aligned} \tag{6}$$

result that:

$$\left.\frac{\mathrm{d}V}{\mathrm{d}\Theta}\right|_{\Theta=\Theta^*} = \Theta \tag{7}$$

Consider that $N \geq 2m$ and

$$\begin{aligned} P(m+d+N) &= \\ [\Psi^T(m+d+N)\Psi(m+d+N]^{-1}, \end{aligned} \tag{8}$$

expression is established:

$$\Theta^{*}(m+d+N-1)= P(m+d+N)\Psi(m+d+N]y(m+d+N), \quad (9)$$

which is a recursive estimator parameters, parameter estimation is obtained by measuring and storing the signals [6].

2.2. Recursive least squares method

Based on recursive estimator equations, recursive algorithm can get:

$$\Theta^{*}(k+1)= \Theta^{*}(k)+\gamma(k)[y(k+1)]-\Psi^{T}(k+1)\Theta^{*}(k)], \quad (10)$$

where, $\Theta^{*}(k)$ and $\Theta^{*}(k+1)$ are estimation corresponding moments *kT*, respectively (*k*+1)*T*, and γ(*k*) is the is the correction vector, and $\Psi^{T}(k+1)\Theta^{*}(k)$ is one-step-ahead prediction for vector y.

The corrector vector has expression:

$$\gamma(k)=P(k+1)\Psi(k+1)= \frac{1}{\Psi^{T}(k+1)P(k)\Psi(k+1)+I}\cdot P(k), \quad (11)$$

where the matrix *P*(*k*+1) is:

$$P(k+1)=[I-\gamma(k)\Psi^{T}(k+1)]P(k). \quad (12)$$

The recursive algorithm is activated by imposing initial conditions:

$$\Theta^{*}(0)=0, \quad P(0)=\alpha I. \quad (13)$$

The probability matrix *P* is influenced by the covariance matrix of the parameter estimates:

$$E[P(k+1)]=\frac{1}{\Gamma e^{2}}\operatorname{cov}[\Delta\Theta(k)], \quad (14)$$

where $\Gamma e^{2}=E(e^{T}e)$ and $\Delta\Theta(k)=\Theta^{*}(k)-\Theta(0)$.

Recursive algorithm convergence is influenced by $P(0)$ and $\Theta^{*}(0)$. The estimation methods have good results if the estimated parameters are non-deviated:

$$E[\Theta^{*}(N)]=\Theta(0), \quad (15)$$

N is finit and with with significant importance:

$$\lim_{N\to\infty}E[\Theta^{*}(N)]=\Theta^{*}(0), \quad \lim_{N\to\infty}E\left\{[\Theta^{*}(N)-\Theta(0)][\Theta^{*}(N)-\Theta^{*}(0)]^{T}\right\}=0. \quad (16)$$

Recursive algorithm convergence is influenced by the $P(0)$ and $\Theta^{*}(0)$ values.

2.3. Least squares extended method

Consider the example:

$$A(z^{-1})y(z)-B(z^{-1})z^{-d}u(z) =D(z^{-1})e(z), \quad (17)$$

where $D(z^{-1})e(z)$ is the corelated error signal.

Least squares extended methods results from combining recursive methods for dynamic processes and stochastic signals:

$$y(k)=\Psi^{T}(k)\Theta^{*}(k-1)+e(k), \quad (18)$$

Where vector $\Psi^{T}(k)$ has expresion:

$$\Psi^T(k) = [-y(k-1)... \\ -y(k-m)u(k-d-1)... \\ u(k-d-m)v^*(k-1)...v^*(k-p) \tag{19}$$

The recursive variation facilitates estimating of parameters that are obtained from the relationship:

$$\Theta^*(k+1) = \Theta^*(k) + \gamma(k)[y(k+1) \\ -\Psi^T(k+1)\Theta^*(k)]. \tag{20}$$

The signal values $e(k)$ are calculated based on the equation (18).

3. Conclusions

Online identification of dynamic processes consists in using a PC what works online simultaneously with the process.

Adaptive controllers [6] are parametric and nonparametric. The first controller the process model is parametric; in case of nonparametric self-tuning controllers, the process has a non-parametric variation.

For self-tuning controllers estimation of unknown parameter is performed independently of the controller design [7]; estimated parameters are considered real, and the estimation errors being out of it.

Recursive algorithms for parameters estimation by discussed methods may be considered as having a unique form:

$$\Theta^*(k+1) = \Theta^*(k) + \gamma(k)e(k+1), \\ \gamma(k) = \mu(k+1)P(k)\Psi(k+1), \\ e(k+1) = y(k+1) - \Psi^T(k+1)\Theta^*(k), \tag{21}$$

the differences are introduced by the vectors of parameters, Θ or data γ.

Least squares method is applied when the order process are known, *m*, and dead time. The input signal, *u* must be measurable, and lasting at least the order *m*, and the output signal can be disrupted by stationary noise. Since the error signal, *e(k)* must be uncorrelated, the method is not applicable to processes with loud noise.

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