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CONSTRAINED SELF-TUNING CONTROL OF STOCHASTIC EXTREMAL SYSTEMS

Vytautas KAMINSKAS, Kęstutis ŠIDLAUSKAS, and Česlovas TALLAT–KELPŠA

Scientific Research Centre "Informatika"
of Vytautas Magnus University
and Lithuanian Academy of Sciences,
233684 Kaunas, Metalo St.4, Lithuania

Abstract. Self-tuning control with recursive identification of extremal dynamic systems is considered. The systems can be represented by combinations of linear dynamic and extremal static parts, their output being disturbed by a coloured noise. Minimum-variance controllers for Hammerstein, Wiener, and Wiener–Hammerstein-type systems are designed taking into consideration restrictions for control signal magnitude and/or change rate. The estimates of unknown parameters in the controller equations are obtained in the identification process in the closed loop. The efficiency of self-tuning control algorithms is illustrated by statistical simulation. On the basis of worked out methods, adaptive systems for optimization of fuel combustion and steam condensation processes in thermal power units are developed.

Key words: stochastic extremal systems, minimum-variance control, self-tuning control, recursive identification.

Introduction. Industrial processes often involve stochastic dynamic systems with extremal characteristics.

The control law synthesis for linear stochastic systems is often based on the minimization of the variance of output signal deviations from the desired value (Åström, 1970; Isermann, 1981). Such an approach deals with the design of an optimal predictor of the controlled object's output and with the control strategy determination according to the equality condition between a corresponding number step-prediction value and a desired one.

In self-tuning control systems the unknown parameters are replaced by their current estimates obtained in the identification process in the closed loop (Isermann, 1981, Åström, 1983).

There are some works in which minimum-variance control laws for extremal dynamic systems are synthesized. Keviczky, Vajk, and Hetthessy (1979) proposed self-tuning minimum-variance control algorithms for single input-single output (SISO) Hammerstein-type systems, Kaminskas and Tallat–Kelpša (1983) developed analogous algorithms for multiple input-single output Hammerstein-type systems taking into account restrictions for the control signal magnitude. Works by Kaminskas and Šidlauskas (1984, 1985) deal with the application of minimum-variance control strategies to SISO Wiener– and Wiener–Hammerstein-type systems. Kaminskas, Tallat–Kelpša, and Šidlauskas (1986, 1987) proposed self-tuning control algorithms for systems of the latter type.

In this paper self-tuning minimum-variance control of SISO stochastic extremal systems with time delay is considered. The systems consist of various interconnections of linear dynamic and extremal static parts. System's outputs are corrupted by disturbances with a general fractional-rational spectral density. Restrictions for control signal magnitude and/or change rate are taken into account.

Problem statement. Discrete-time extremal dynamic systems are considered with an observed output signal y_t, defined by

$$y_t = W_2(z^{-1};\boldsymbol{\beta})f(v_t;\boldsymbol{\theta}) + H(z^{-1};\mathbf{h})\xi_t, \tag{1}$$

$$v_t = W_1(z^{-1};\boldsymbol{\alpha})z^{-\tau}u_t, \tag{2}$$

where u_t is an observed input (control) signal; ξ_t – an unobserved white noise sequence with a zero mean and a finite variance σ_ξ^2 ;

$$f(v_t;\boldsymbol{\theta}) = \theta_1 v_t + \theta_2 v_t^2 \tag{3}$$

is an extremal characteristic of the static element with parameters $\boldsymbol{\theta}^T = (\theta_1, \theta_2)$, $\theta_2 \neq 0$;

$$W_1(z^{-1};\boldsymbol{\alpha}) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{\sum_{i=0}^{n_b} b_i z^{-i}}{1 + \sum_{i=1}^{n_a} a_i z^{-i}}, \tag{4}$$

$$W_2(z^{-1};\boldsymbol{\beta}) = \frac{D(z^{-1})}{G(z^{-1})} = \frac{\sum_{i=0}^{n_d} d_i z^{-i}}{1 + \sum_{i=1}^{n_g} g_i z^{-i}}, \tag{5}$$

$$H(z^{-1};\mathbf{h}) = \frac{P(z^{-1})}{R(z^{-1})} = \frac{1 + \sum_{i=1}^{n_p} p_i z^{-i}}{1 + \sum_{i=1}^{n_r} r_i z^{-i}} \tag{6}$$

are fractional-rational transfer functions of linear dynamic parts of the control channel (W_1 and W_2) and of the disturbance channel (H) with parameters

$$\left.\begin{aligned} \boldsymbol{\alpha}^T &= (a_1, a_2, \ldots, a_{n_a}, b_0, b_1, \ldots, b_{n_b}) \\ \boldsymbol{\beta}^T &= (g_1, g_2, \ldots, g_{n_g}, d_0, d_1, \ldots, d_{n_d}) \\ \mathbf{h}^T &= (r_1, r_2, \ldots, r_{n_r}, p_1, p_2, \ldots, p_{n_p}) \end{aligned}\right\}; \tag{7}$$

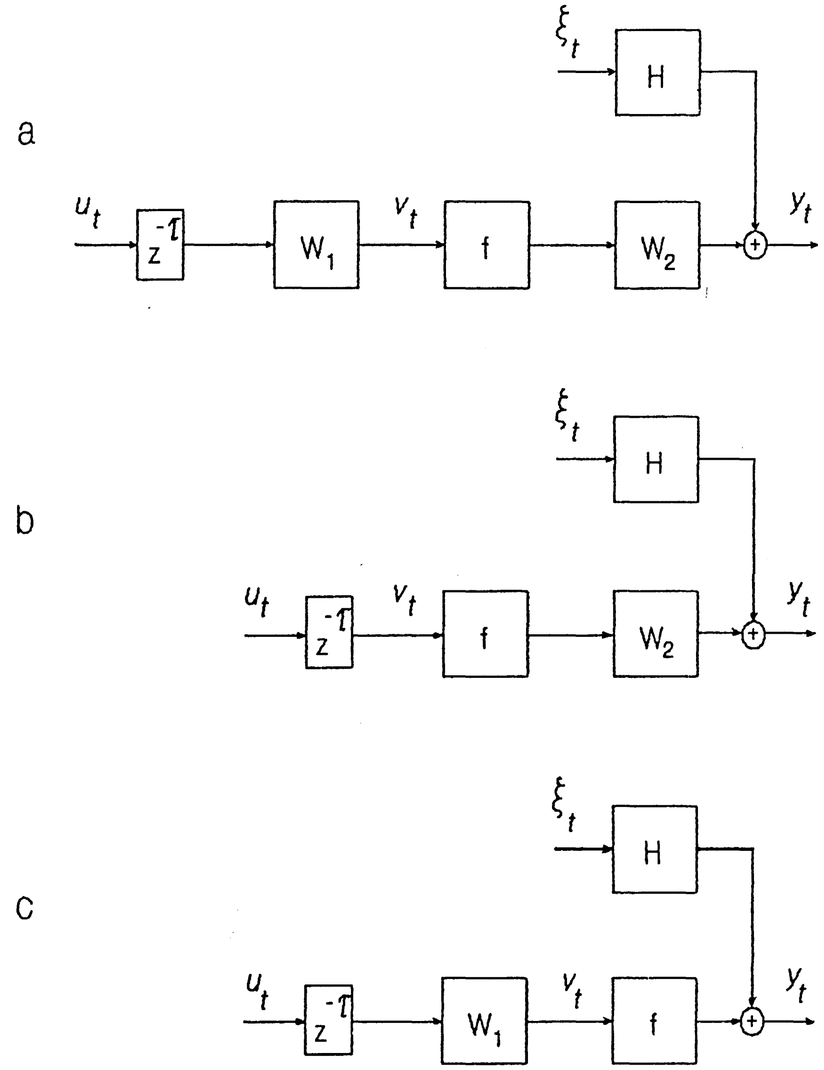

Fig. 1. Stochastic extremal systems of Wiener–Hammerstein (a), Hammerstein (b), and Wiener (c) types.

z^{-i} is an i-step backward time-shift operator; τ represents pure delay of the system; t is a time index; T denotes transposition.

The equations (1)–(3) specify the most general class of stochastic extremal systems with the extremal static element standing between two linear dynamic parts and the system's output being disturbed by a coloured noise with a general fractional-rational spectral density (see Fig. 1, a). Such systems are usually called stochastic extremal Wiener–Hammerstein-type systems. In particular cases, by removing the first linear dynamic part, stochastic extremal Hammerstein-type systems are obtained (Fig. 1, b) and, by removing the second linear dynamic part, we obtain stochastic extremal Wiener-type systems (Fig. 1, c).

We assume that the control and disturbance channels are stable and minimum-phase, the polynomials in the numerator and the denominator of each of the transfer functions (4)–(6) have no common roots, the linear dynamic parts in the control channel have a unit gain:

$$W_1(1;\boldsymbol{\alpha}) = W_2(1;\boldsymbol{\beta}) = 1\ , \tag{8}$$

and the parameters $\mathbf{c}^T = (\boldsymbol{\alpha}^T, \boldsymbol{\beta}^T, \mathbf{h}^T, \boldsymbol{\theta}^T)$ of the system (1)–(3) are unknown (though the orders $n_a, n_b, n_g, n_d, n_r, n_p$ and the time delay τ are known).

Let it be required to drive the system (1)–(3) from an initial state (u_0, y_0) to the steady state of the extremal operation

$$y^* = f(u^*;\boldsymbol{\theta}) = -\frac{\theta_1^2}{4\theta_2}, u^* = \arg\operatorname*{extr}_x f(u;\boldsymbol{\theta}) = -\frac{\theta_1}{2\theta_2}, \tag{9}$$

and to ensure the minimum variance of the errors arising due to uncontrolled disturbances. Therefore, the optimal current control signal u_{t+1}^* at the discrete time t must be determined from the condition

$$u^*_{t+1} : Q_t(u_{t+1}) = M[y_{t+\tau+1} - y^*]^2 \to \min_{u_{t+1}\in\Omega_u} , \tag{10}$$

where

$$\Omega_u = \left\{u_{t+1} : u_{\min} \le u_{t+1} \le u_{\max} , |u_{t+1} - u^*_t| < \delta_t\right\} \tag{11}$$

is the domain of admissible control values characterized by restrictions for the control signal magnitude ($u_{\min}, u_{\max}$) and/or change rate ($\delta_t > 0$) often arising in practice; M is the sign of mathematical expectation.

The system parameters being unknown, it is impossible to obtain the optimal current control value (10). If the genuine parameters $\mathbf{c}$ are replaced by their current estimates $\widehat{\mathbf{c}}^T_t = (\widehat{\boldsymbol{\alpha}}^T_t, \widehat{\boldsymbol{\beta}}^T_t, \widehat{\mathbf{h}}^T_t, \widehat{\boldsymbol{\theta}}^T_t)$ determined from the condition

$$\widehat{\mathbf{c}}_t = \arg\min_{\mathbf{c}\in\Omega_c} \widetilde{Q}_t(\mathbf{c}), \tag{12}$$

$$\widetilde{Q}_t(\mathbf{c}) = \frac{1}{t}\sum_{k=1}^{t}[y_k - y_{k|k-1}(\mathbf{c})]^2 , \tag{13}$$

the self-tuning system, including control and identification algorithms, can provide only the minimum value of the asymptotic variance

$$Q(u_{t+1}) = M[y_{t+\tau+1} - \widehat{y}^*_t]^2 \to \min_{u_{t+1}\in\Omega_u} , t \to \infty , \tag{14}$$

where

$$\begin{aligned} y_{t|t-1}(\mathbf{c}) = z[1 - H^{-1}(z^{-1};\mathbf{h})]y_{t-1} \\ +H^{-1}(z^{-1};\mathbf{h})W_2(z^{-1};\boldsymbol{\beta})f[W_1(z^{-1};\boldsymbol{\alpha})z^{-\tau}u_t;\boldsymbol{\theta}] , \end{aligned} \tag{15}$$

is the optimal (in the sense of a minimum error variance) one-step ahead prediction of the output signal y_t at the discrete time $t-1$ (Kaminskas, 1985); Ω_c is the admissible domain for the parameters $\mathbf{c}$, defined by stability, minimum-phase and unit gain conditions, $\widehat{y}_t^*$ is the current estimate of y^* obtained by inserting $\widehat{\boldsymbol{\theta}}_t$ into (9).

Thus, a self-tuning controller design requires two problems to be solved: minimum-variance controller synthesis on the assumption that system parameters are known and identification of the controlled system in a closed loop.

Minimum-variance controllers. The transfer function (6) of the disturbance channel can be expressed as a sum of two components (Åström, 1970; Isermann, 1981):

$$H(z^{-1};\mathbf{h}) = \frac{P(z^{-1})}{R(z^{-1})} = E(z^{-1}) + z^{-(\tau+1)}\frac{L(z^{-1})}{R(z^{-1})}\,, \tag{16}$$

where

$$E(z^{-1}) = 1 + e_1 z^{-1} + \ldots + e_{n_e} z^{-n_e}\,, \tag{17}$$

$$L(z^{-1}) = l_0 + l_1 z^{-1} + \ldots + l_{n_l} z^{-n_l}\,, \tag{18}$$

$$n_e = \begin{cases} \tau, & \text{if } n_r > 0, \\ \min\{\tau, n_p\}, & \text{if } n_r = 0, \end{cases} \tag{19}$$

$$n_l = \max\{n_r,\ n_p - \tau\} - 1\,. \tag{20}$$

Then the output signal of the system may be represented as

$$y_{t+\tau+1} = y_{t+\tau+1|t}(\mathbf{c}) + E(z^{-1})\xi_{t+\tau+1}\,, \tag{21}$$

where

$$\begin{aligned} y_{t+\tau+1|t} &= z^{\tau+1}[1 - \widetilde{H}^{-1}(z^{-1};\mathbf{h})]y_t \\ &+ \widetilde{H}^{-1}(z^{-1};\mathbf{h})W_2(z^{-1};\boldsymbol{\beta})f[W_1(z^{-1};\boldsymbol{\alpha})u_{t+1};\boldsymbol{\theta}] \end{aligned} \tag{22}$$

is a $(\tau+1)$-step ahead optimal prediction of the output signal at the discrete time t;

$$\widetilde{H}^{-1}(z^{-1};\mathbf{h}) = E(z^{-1})H^{-1}(z^{-1};\mathbf{h}) \ . \tag{23}$$

In accordance with (21), the control performance criterion (10) can be transformed into

$$Q_t(u_{t+1}) = M[y_{t+\tau+1}(\mathbf{c}) - y^*]^2 + \Big(1 + \sum_{i=1}^{n_e} e_i^2\Big)\sigma_\xi^2 \ . \tag{24}$$

Therefore, the optimal current control signal u_{t+1}^* at the discrete time t may be determined from the condition

$$u_{t+1}^* = \arg \min_{u_{t+1}\in\Omega_u} M[y_{t+\tau+1|t}(\mathbf{c}) - y^*]^2 \ . \tag{25}$$

Further simple transformations yield the minimum-variance controller equation for stochastic extremal Wiener–Hammerstein-type systems (Kaminskas and Šidlauskas, 1985; Kaminskas, 1986):

$$u_{t+1}^* = \begin{cases} \min\{u_{\max}, u_t^* + \delta_t, \widetilde{u}_{t+1}\}, & \text{if } \widetilde{u}_{t+1} \geq u_t^*, \\ \max\{u_{\min}, u_t^* - \delta_t, \widetilde{u}_{t+1}\}, & \text{if } \widetilde{u}_{t+1} < u_t^*, \end{cases} \tag{26}$$

where

$$\widetilde{u}_{t+1} = W_1^{-1}\Big(z^{-1};\boldsymbol{\alpha}\Big)\Big(-\frac{\theta_1}{2\theta_2} \pm \sqrt{\max\{0,\nu_t\}}\Big) \ , \tag{27}$$

$$\nu_t = \frac{1}{\theta_2}\Big[W_2^{-1}\Big(z^{-1};\boldsymbol{\beta}\Big)\Big(q_t + \widetilde{y}_t\Big) - y^*\Big] \ , \tag{28}$$

$$\widetilde{y}_k = \begin{cases} y^*, & \text{if } k = t \ , \\ y_{k+\tau+1|k}(\mathbf{c}), & \text{if } k = t-1, t-2, \dots \ , \end{cases} \tag{29}$$

and

$$\begin{aligned} q_t =& z^{\tau+1}\Big[1 - \widetilde{H}(z^{-1};\mathbf{h})\Big]\varepsilon_{t|t-\tau-1}(\mathbf{c}) \\ =& z^{\tau+1}\Big[E(z^{-1}) - H(z^{-1};\mathbf{h})\Big]\varepsilon_{t|t-1}(\mathbf{c}). \end{aligned} \tag{30}$$

In the latter equation

$$\varepsilon_{t|t-\tau-1}(\mathbf{c}) = y_t - y_{t|t-\tau-1}(\mathbf{c}) = E(z^{-1})\varepsilon_{t|t-1}(\mathbf{c}) \tag{31}$$

is the $(\tau+1)$–step prediction error at the discrete time $t-\tau-1$, and

$$\varepsilon_{t|t-1}(\mathbf{c}) = y_t - y_{t|t-1}(\mathbf{c}) \tag{32}$$

represents the one-step prediction error at the time $t-1$.

Introducing $W_1(z^{-1};\boldsymbol{\alpha}) \equiv 1$ into equation (27) gives us

$$\widetilde{u}_{t+1} = -\frac{\theta_1}{2\theta_2} \pm \sqrt{\max\{0, \nu_t\}}\ , \tag{33}$$

and (26), (33), (28)–(30) are the minimum-variance controller equations for extremal Hammerstein-type systems (Kaminskas and Tallat–Kelpša, 1983; Kaminskas, 1986).

Similarly, in the case of $W_2(z^{-1};\boldsymbol{\beta}) \equiv 1$, we obtain

$$\nu_t = \frac{1}{\theta_2}\Big(q_t + \widetilde{y}_t - y^*\Big)\ , \tag{34}$$

and therefore, (26), (27), (34), (29), (30) are the minimum-variance controller equations for extremal Wiener-type systems (Kaminskas and Šidlauskas, 1984; Kaminskas, 1986).

The alternate sign $+/-$ in controller equations (27),(33) precedes the square root operation, indicating that $\widetilde{u}_{t+1}$ is obtained as the solution of a quadratic equation. The sign must be selected so that signal magnitude and change rate restrictions were violated as little as possible.

The sequence q_t is a realization of an autoregressive-moving average process because it can be defined as

$$q_t = z^{\tau+1}\Big[E(z^{-1}) - H(z^{-1};\mathbf{h})\Big]\xi_t \, . \tag{35}$$

Therefore, at random discrete time moments k with $\nu_k < 0$ the feedback is interrupted. If the restrictions (11) are not taken into account, we have $u_t^* \equiv \widetilde{u}_t$, and the control error sequence can be represented as

$$\begin{aligned} \widetilde{e}_t &= y_t - y^* \\ &= \begin{cases} z\Big[W_2(z^{-1};\boldsymbol{\beta}) - d_0\Big] \\ \quad\times f\Big[W_1(z^{-1};\boldsymbol{\alpha})z^{-\tau}u_{t-1};\boldsymbol{\theta}\Big] \\ \quad -y^*(1-d_0) + H(z^{-1};\mathbf{h})\xi_t, & \text{if } \nu_{t-1} < 0 \, , \\ E(z^{-1})\xi_t, & \text{if } \nu_{t-1} \geqslant 0 \, . \end{cases} \end{aligned} \tag{36}$$

The control error sequence in the case of a Wiener-type system can be expressed in a less complex form:

$$\widetilde{e}_t = \begin{cases} \min\{E(z^{-1})\xi_t, H(z^{-1};\mathbf{h})\xi_t\}, & \text{if } \theta_2 < 0 \, , \\ \max\{E(z^{-1})\xi_t, H(z^{-1};\mathbf{h})\xi_t\}, & \text{if } \theta_2 > 0 \, . \end{cases} \tag{37}$$

If the control signal is restricted, it is impossible to obtain an analytical expression for control error sequence.

Identification in the closed loop. The current estimates $\widehat{\mathbf{c}}_t$, used instead of the unknown parameters $\mathbf{c}$ of the system (1)–(3) in the minimum-variance controller equations (26)–(30), (33), (34), are obtained in the identification process in the closed loop by the following recursive algorithm (Kaminskas, 1982):

$$\widehat{\mathbf{c}}_{t+1} = \widehat{\mathbf{c}}_t + \gamma_{t+1}\Delta\mathbf{c}_t \, , \Delta\mathbf{c}_t = -\mathbf{k}_{t+1}\varepsilon_{t+1|t}(\widehat{\mathbf{c}}_t) \, , \tag{38}$$

$$\gamma_{t+1} = \max\{1, \gamma_{t+1}^{\max} - \delta_\gamma\} \ , \tag{39}$$

where

$$\mathbf{k}_{t+1} = \frac{\mathbf{T}_t \boldsymbol{\lambda}_{t+1}}{\boldsymbol{\lambda}_{t+1}^T \mathbf{T}_t \boldsymbol{\lambda}_{t+1}} \ , \tag{40}$$

$$\mathbf{T}_{t+1} = \left[\mathbf{I} - \mathbf{k}_{t+1} \boldsymbol{\lambda}_{t+1}^T\right] \mathbf{T}_t, \quad \mathbf{T}_0 = \mathbf{I} \ , \tag{41}$$

$$\begin{aligned} \boldsymbol{\Pi}_{t+1} =& \boldsymbol{\Pi}_t - \mathbf{k}_{t+1} \boldsymbol{\lambda}_{t+1}^T \boldsymbol{\Pi}_t - \boldsymbol{\Pi}_t \boldsymbol{\lambda}_{t+1} \mathbf{k}_{t+1}^T + \\ &+ \left[1 + \boldsymbol{\lambda}_{t+1}^T \boldsymbol{\Pi}_t \boldsymbol{\lambda}_{t+1}\right] \mathbf{k}_{t+1} \mathbf{k}_{t+1}^T, \quad \boldsymbol{\Pi}_0 = 0 \end{aligned} \tag{42}$$

for $t < n_c$, or

$$\mathbf{k}_{t+1} = \frac{\boldsymbol{\Pi}_t \boldsymbol{\lambda}_{t+1}}{1 + \boldsymbol{\lambda}_{t+1}^T \boldsymbol{\Pi}_t \boldsymbol{\lambda}_{t+1}} \ , \tag{43}$$

$$\boldsymbol{\Pi}_{t+1} = \left[\mathbf{I} - \mathbf{k}_{t+1} \boldsymbol{\lambda}_{t+1}^T\right] \boldsymbol{\Pi}_t \tag{44}$$

for $t \geqslant n_c$; $\boldsymbol{\lambda}_{t+1} = \nabla_c \varepsilon_{t+1|t}(\widehat{\mathbf{c}}_t)$ is the current value of a prediction error $\varepsilon_{t+1|t}(\mathbf{c})$ gradient; γ_{t+1} is a scalar factor, ensuring the presence of an estimate trajectory within the admissible area Ω_c, as $\gamma_{t+1}^{\max} ||\Delta \mathbf{c}_t||$ is the distance in the direction $\Delta \mathbf{c}_t$ from the point $\widehat{\mathbf{c}}_t$ to the boundary of this area; $\mathbf{O}$, $\mathbf{I}$ are the zero and identity matrices correspondingly, their dimensions being $n_c \times n_c$; $n_c = n_a + n_b + n_g + n_d + n_r + n_p + 4$ is the number of the unknown parameters; δ_γ is a small positive constant; $||\ ||$ is the Euclidian norm sign.

The identification algorithm (38)–(44) is derived by means of the quasi-linearization of the one-step prediction error (32) in (13). In this algorithm the pseudoinversion technique is used at the initial steps and later, when the number of control steps exceeds n_c, a common inversion of the corresponding matrices is performed.

The admissible area Ω_c is a set of such parameter values which provide stable and minimum-phase transfer functions of control and disturbance channels in (15) and convex characteristic (3). Different modifications and properties of recursive

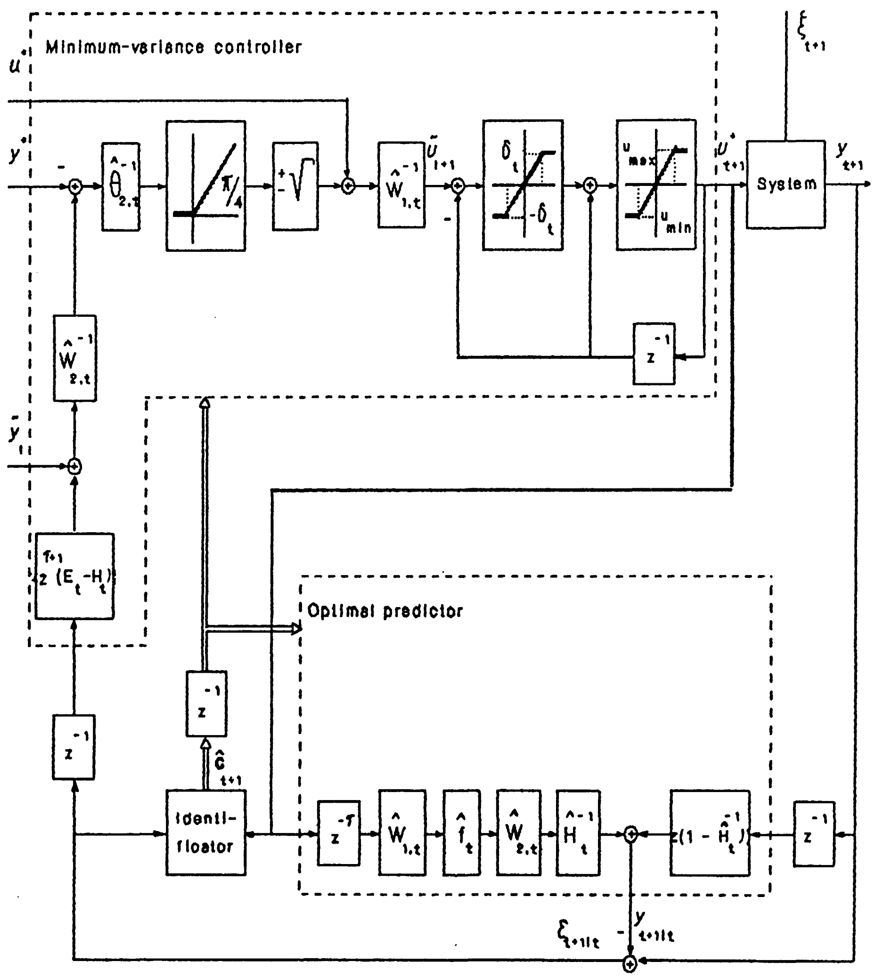

Fig. 2. The diagram of self-tuning minimum-variance control system.

algorithms of the same kind as (38),(39) were considered by Kaminskas (1982).

The control and identification algorithms employ the prediction error (32) as the input information. This property is illustrated by Fig. 2, where a self-tuning minimum-variance control system for stochastic extremal Wiener–Hammerstein-type systems is shown.

Simulation results. Because of the nonlinear characteristics of the system (1)–(3) and of the minimum-variance controllers, an analytical investigation of the self-tuning control system properties becomes complex. For this reason, the efficiency of selftuning algorithms was examined by means of a statistical simulation using typical examples of extremal systems under discussion.

In this work the self-tuning control process is illustrated on the example of a stochastic extremal Wiener–Hammerstein-type system

$$\left.\begin{aligned} y_t &= \frac{1.6}{1+0.6z^{-1}}(2v_t - v_t^2) + \frac{1}{1-0.85z^{-1}}\xi_t \\ v_t &= \frac{0.6}{1-0.4z^{-1}} z^{-2} u_t \end{aligned}\right\} . \tag{45}$$

The current estimates of the system parameters were calculated by means of the component version of the recursive identification algorithm (38)–(44) with the initial zero values (Kaminskas, 1982). The control signal was determined according to the algorithm (26)–(30) in which the unknown parameters were substituted by their current estimates. The admissible area for the control signal was

$$u_{\min} = -1\,, \quad u_{\max} = 3\,, \quad \delta_t = \delta = 4\,. \tag{46}$$

Fig. 3 illustrates the identification process in the closed loop. The sign before the square root in (26)–(30) was being

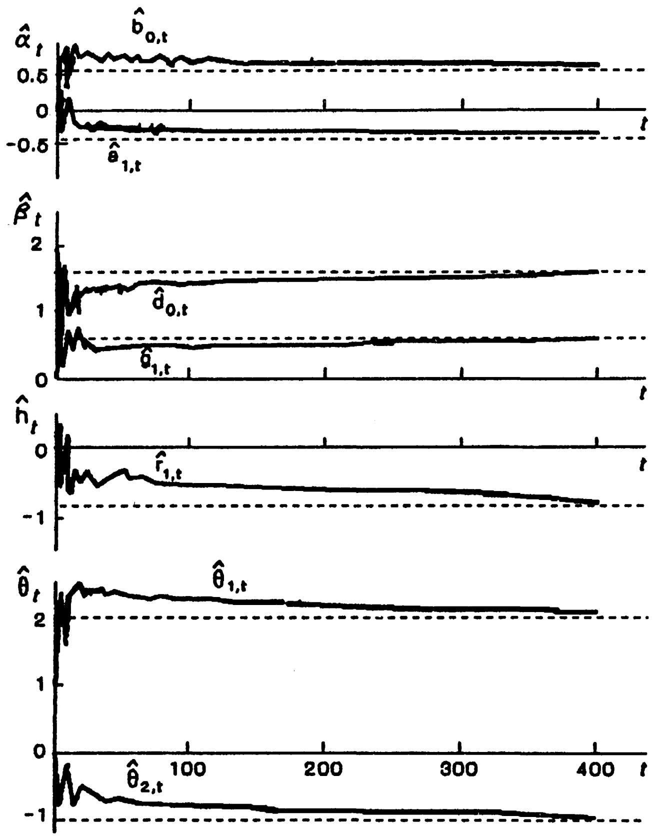

Fig. 3. The convergence of current parameter estimates for the system (45) in the self-tuning control process.

constantly alternated with the purpose of improving the convergence of parameter estimates (thus the informativity of the input (control) signal was increased).

In Fig. 4 the estimates of control error autocovariance functions are shown. Fig. 5 demonstrates the diagrams of control and output signals. The stages I and II represent a self-tuning control process. At the first (initial) stage parameter estimation errors are large and at the second stage parameter

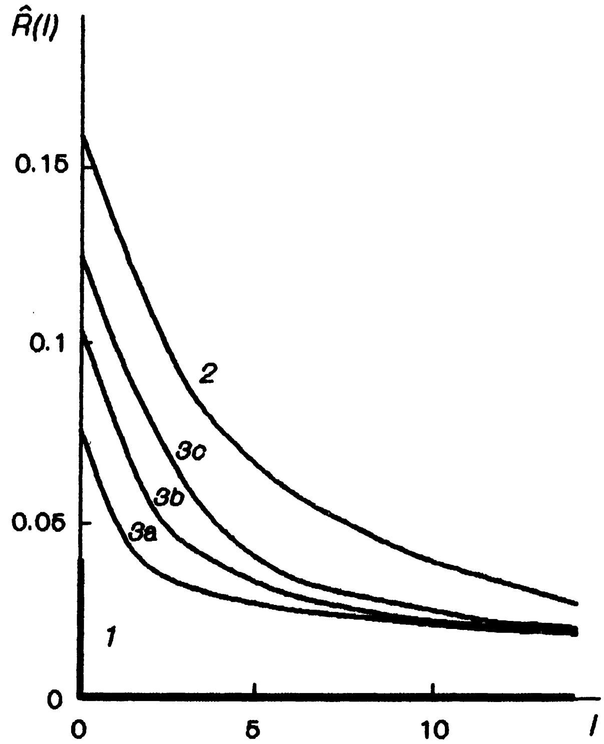

Fig. 4. The autocovariance function estimates for the system (45): 1 – for the white noise, 2 – for the disturbances at the output, 3 – for the control error: a – control with genuine system parameters without restrictions (46), b – self-tuning control without restrictions (46), c – self-tuning control with restrictions (46).

estimates are close to their genuine values in (45). The stage III illustrates the case of the self-tuning controller being disconnected, i.e., the argument value u^* of the extremal characteristic being applied to the input. Control efficiency degrades because the compensation of uncontrolled disturbances is terminated.

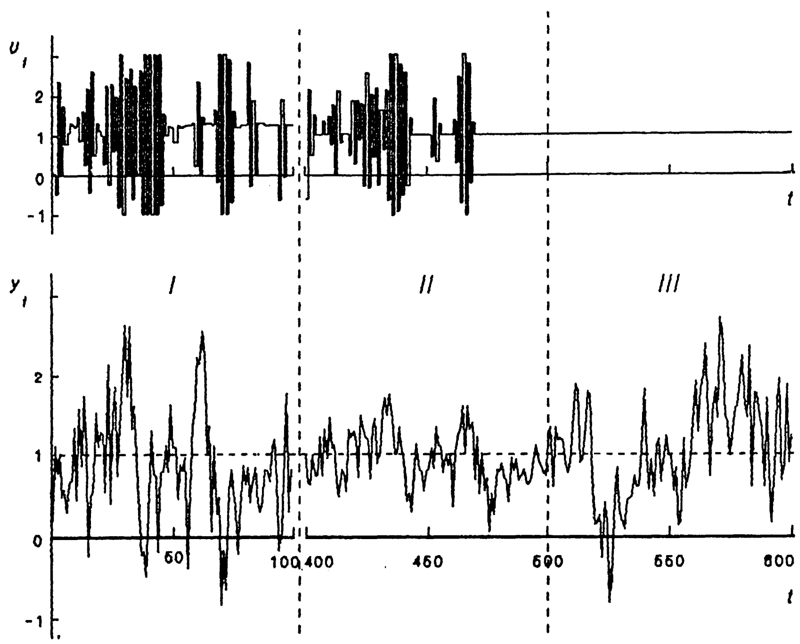

Fig. 5. Processes in the system (45) under self-tuning control.

Application. The designed self-tuning control algorithms were applied for the optimization of fuel combustion and steam condensation processes in power units of a thermal power plant. The main characteristics of power unit subsystems are for the most extremal. In the course of operation process these characteristics change due to the ageing of equipment, contamination of working surfaces and under the influence of other uncontrolled disturbances. Therefore, it is possible to provide optimal operation regimes for separate subsystems and for the whole power unit only by applying self-tuning control. The control aim is to minimize the deviations of the given to a user active power from its highest possible value at a fixed fuel expenditure level.

In Fig. 6 the results of a numerical experiment on self-

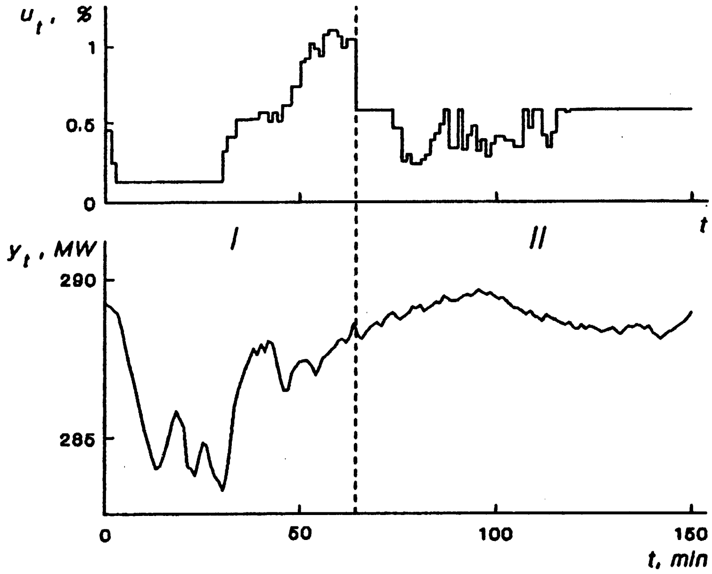

Fig. 6. The results of a numerical experiment on self-tuning control of fuel combustion process.

tuning control of a fuel combustion process in a power unit are given. The control is executed by means of changing the fan wings angle, influencing the oxygen concentration in smoke gases, the latter being considered as an input signal. The active power given to a user (pure power) is considered as the output signal.

According to the results of the first stage of experiment (I), the controlled plant model from real data is designed in the form of a stochastic extremal Hammerstein-type system

$$u_t = \frac{0.16}{1 - 0.83z^{-1}}(286.8 + 3.05u_t - 3.4u_t^2) + \frac{1 + 0.44z^{-1}}{1 - 0.97z^{-1}}\xi_t \,, \tag{47}$$

where u_t is the oxygen concentration (%); and y_t is the pure power (MW). Off-line identification algorithms (Kaminskas,

1985) and pseudorandom input sequences are used for this purpose.

At the second stage (II) self-tuning control of a fuel combustion process, described by (47), is simulated using a computer. The self-tuning control algorithms (26)–(30), (38)–(44) are applied.

Conclusions. Methods for self-tuning control of SISO stochastic extremal systems with time delay are considered. The systems can be represented as various interconnections of linear dynamic and extremal static parts. The system output is disturbed by a coloured noise. The technique of minimum-variance controller synthesis for these systems, considering possible restrictions for control signal magnitude and/or change rate is presented. Parametric identification algorithms in the closed loop are designed to estimate the unknown parameters in the controller equations.

Convergence of self-tuning control algorithms is shown experimentally. On the basis of the proposed methods adaptive systems for optimization of processes in power units are being designed.

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V. Kaminskas was born in 1946. He graduated from the Department of Automatics of the Kaunas Polytechnical Institute in 1968. He received the Candidate Degree in Technical Sciences in 1972, and the Doctor Degree in Technical Sciences in 1983. In 1984 he was awarded the title of the Professor. From 1968 until 1989 he worked at the Physical and Technical Energy Research Institute of the Lithuanian Academy of Sciences. Now he is the Director of the Scientific Research Centre "Informatika" of Vytautas Magnus University and Lithuanian Acad. of Sci. His research interests are in the areas of dynamic system identification and adaptive computer controlled systems. He is the author of 4 monographs and about 150 scientific papers on these topics.

K. Šidlauskas was born in 1955. He graduated from the Department of Automatics of the Kaunas Polytechnical Institute in 1978. He received the Candidate Degree in Technical Sciences in 1986. From 1978 until 1989 he worked at the Kaunas Polytechnical Institute and at the Physical and Technical Energy Research Institute. Now he is a senior research worker at the Scientific Centre "Informatika". His research interests include self-tuning control of nonlinear dynamic systems.

Č. Tallat–Kelpša was born in 1953. He graduated from the Department of Automatics of the Kaunas Polytechnical Institute in 1976. He received the Candidate Degree in Technical Sciences in 1983. From 1976 until 1989 he worked at the Physical and Technical Energy Research Institute, and now he is a senior research worker at the Scientific Centre "Informatika". His research interests are in the areas of extremal dynamic system identification and power plant control.