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PRACTICAL ISSUES IN THE IMPLEMENTATION OF PREDICTOR-BASED SELF-TUNING CONTROL SYSTEMS

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Abstract. Design problems of predictor-based self-tuning digital control systems for different kinds of linear and non-linear dynamical plants are discussed. Special cases include linear plants with unstable and nonminimum-phase control channels, linear plants with inner feedbacks, nonlinear Hammerstein and Wiener-Hammerstein-type plants. Considered are control systems based on generalized minimum variance algorithms with amplitude and introduction rate restrictions for the control signal.

Key words: predictor-based self-tuning control, generalized minimum variance control.

1. Introduction. Usually control system design must take into account the fact that a priori information about the plant and its environment is insufficient. Control system must also be capable of ensuring the control task despite variations in plant's dynamic and static characteristics, provoked by inner and outer disturbances. Different modifications of self-tuning control systems can be successfully used in order to cope with these requirements (Isermann, 1981; Åström, 1983; Åström and Wittenmark, 1984).

Self-tuning control system usually consists of two loops. Control plant and the controller form the so-called main loop. The second loop may be called the tuning loop, and its aim is to change the control law so as to get adjusted to the unknown situation and to accomplish the control task. Different synthesis methods for the latter loop make it possible to group self-tuning control systems into explicit and implicit ones. An explicit self-tuning control system is based on the estimation of an explicit control plant model, while an implicit one is based on implicit estimation of the controller parameters.

This paper considers practical issues in the implementation of a kind of explicit self-tuning control systems – predictor-based systems (Peterka, 1984; Kaminskas, 1988). In this case explicit control plant model is constructed in the form of an optimal predictor of the output signal. Self-tuning control systems of this kind can be successfully applied to different dynamical control plants (Kaminskas *et al.*, 1988, 1990, 1991).

This paper is intended to give practical recommendations in design of self-tuning predictor-based control systems based on a generalized minimum variance controller with amplitude and introduction rate restrictions for the control signal. For this purpose a general framework of a predictor-based self-tuning control system is presented first, and then special cases are discussed. Special cases include plants with unstable or nonminimum-phase control channel, plants with inner feedbacks and nonlinear Hammerstein and Wiener-Hammerstein-type plants.

2. General framework. First of all we'll show the design process for a predictor-based self-tuning control system in case of a common linear dynamical plant, its operation being defined by the following difference equations

$$y_t = W_0(z^{-1})u_{t-r} + H(z^{-1})\xi_t, \tag{1}$$

where

$$W_0(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})},$$

$$A(z^{-1}) = 1 + \sum_{j=1}^{n_a} a_j z^{-j}, \qquad B(z^{-1}) = \sum_{j=0}^{n_b} b_j z^{-j}, \tag{2}$$

$$H(z^{-1}) = \frac{P(z^{-1})}{R(z^{-1})},$$

$$P(z^{-1}) = 1 + \sum_{j=1}^{n_p} p_j z^{-j}, \qquad R(z^{-1}) = 1 + \sum_{j=1}^{n_r} r_j z^{-j} \tag{3}$$

are fractional-rational transfer functions of the minimum-phase and stable channels of the control signal u_t and the disturbance ξ_t, their numerator and denominator polynomials having no common roots; z^{-i} is an i-step backward-shift operator; y_t is an observable output signal; ξ_t is a sequence of independent random variables with zero mean and a finite variance σ_ξ^2; τ is pure delay value in the control channel. The structural diagram of such a plant is given in Fig. 1.

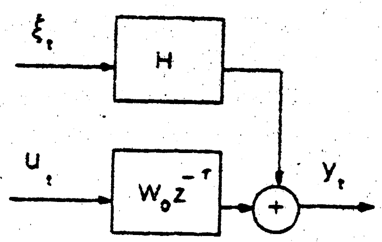

Fig. 1. Structural diagram of a common linear control plant.

The output signal of the control plant (1) can be rewritten as the sum of two components (Kaminskas, 1988)

$$y_{t+\tau+1} = y_{t+\tau+1|t}(\mathbf{c}) + \zeta_{t+\tau+1}, \tag{4}$$

$$y_{t+\tau+1|t} = z^{\tau+1}\left[1 - \widetilde{H}^{-1}(z^{-1})\right] y_t + \widetilde{H}^{-1}(z^{-1}) W_0(z^{-1}) u_{t+1} \tag{5}$$

is optimal $(\tau+1)$-step prediction of the output signal, and the following relationships are true (Åström, 1970)

$$\widetilde{H}(z^{-1}) = E^{-1}(z^{-1}) H(z^{-1}),$$

$$P(z^{-1}) = R(z^{-1}) E(z^{-1}) + z^{-(\tau+1)} L(z^{-1}), \tag{6}$$

$$E(z^{-1}) = 1 + \sum_{i=1}^{n_e} e_i z^{-i}, \qquad L(z^{-1}) = \sum_{i=0}^{n_l} l_i z^{-i}, \tag{7}$$

$$\zeta_t = E(z^{-1}) \xi_t, \qquad \sigma_\zeta^2 = \left(1 + \sum_{i=1}^{n_e} e_i\right) \sigma_\xi^2, \tag{8}$$

$$n_e = \begin{cases} \tau, & \text{if } n_r > 0, \\ \min\{\tau, n_p\}, & \text{if } n_r = 0, \end{cases} \qquad n_l = \max\{n_r, n_p - \tau\} - 1. \qquad (9)$$

$\mathbf{c}^T = (a_1, .., b_0, .., p_1, .., r_1 \ldots)$ is the parameter vector for the control plant (1).

We consider the control plant to be a stochastic one in order to be able to evaluate and to cope with the effect of external disturbances on plant's characteristics. Besides, such a model is capable of smoothing possible model matching errors.

In case of a stochastic control plant it is natural to demand for the control system to provide the minimum variance of the deviations of the observed sequence y_t from the reference sequence y_t^*. Sometimes it is preferable to apply a generalized minimum variance control algorithm, obtained by introducing control costing (Clarke *et al.*, 1987). In this case the control criterion is

$$Q_t(u_{t+1}) = M\{(y_{t+\tau+1} - y^*_{t+\tau+1})^2 + q_t(u_{t+1} - \widetilde{u}^*_{t+1})^2\}, \qquad (10)$$

and optimal control values are

$$u^*_{t+1} = \arg\min_{u_{t+1} \in \Omega_u} Q_t(u_{t+1}), \qquad (11)$$

where

$$\Omega_u = \{u_{t+1} : u_{\min} \leqslant u_{t+1} \leqslant u_{\max}, \quad |u_{t+1} - u_t^*| < \delta_t\} \qquad (12)$$

is the admissible domain for the control values; $u_{\min}$, $u_{\max}$ are control signal boundaries; $\delta_t > 0$ are the restriction values for the introduction rate of the control signal; $y^*_{t+\tau+1}$ marks the reference trajectory for the output signal; $\widetilde{u}_t^*$ marks the reference trajectory for the control signal; q_t is a weight coefficient.

The main reasons for using a generalized minimum variance control algorithm are:

1) Its capability to cope with nonminimum-phase control plants.

2) The possibility to reduce control signal variations by introducing additional restrictions. This is often a welcome fact, though this reduction is usually achieved by loosing in the control quality.

Solution of the extremal problem (11) requires the knowledge of genuine plant parameters **c**. Since these parameters are usually a priori unknown and vary in the operation process, current estimates $\hat{\mathbf{c}}_t$ can be used instead of genuine parameters. The estimates can be obtained in the identification process from the condition

$$\hat{\mathbf{c}}_t:\ \widetilde{Q}_t(\mathbf{c}) = \frac{1}{t}\sum_{l=1}^{t}\varepsilon^2_{l|l-1}(\mathbf{c}) \to \min_{\mathbf{c}\in\Omega_{\mathbf{c}}}, \tag{13}$$

where $\Omega_{\mathbf{c}}$ is the admissible domain for the parameters **c**, usually the same as the stability domain for the closed-loop system;

$$\varepsilon_{t+1|t}(\mathbf{c}) = y_{t+1} - y_{t+1|t}(\mathbf{c}) \tag{14}$$

is the error of one-step-prediction of the output signal, obtained in accordance with

$$\begin{aligned} y_{t+1|t}(\mathbf{c}) &= z\left[1 - H^{-1}(z^{-1})\right]y_t + H^{-1}(z^{-1})W_0(z^{-1})u_{t+1-\tau} \\ &= z\left[H(z^{-1}) - 1\right]\varepsilon_{t|t-1}(\mathbf{c}) + W_0(z^{-1})u_{t+1-\tau}\ . \end{aligned} \tag{15}$$

Thus we arrive at an explicit predictor-based self-tuning control system, its structural diagram given in Fig. 2.

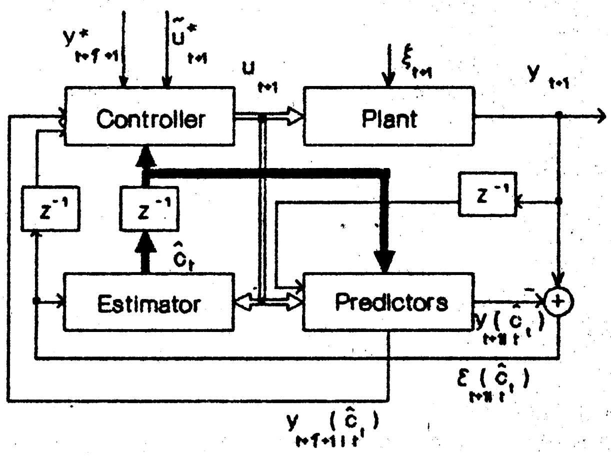

Fig. 2. Structural diagram of predictor-based self-tuning control system.

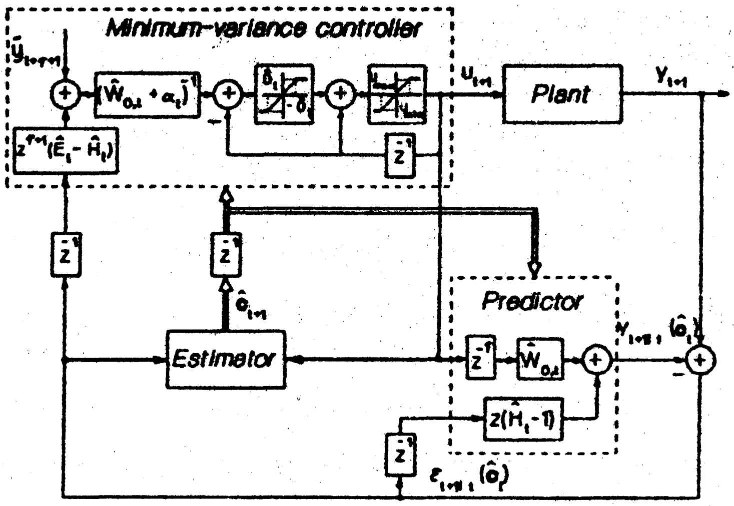

Fig. 3. Block diagram of the self-tuning control system for common linear plants.

Under this approach control and estimation processes are interconnected by a common value – the one-step-prediction error for the output signal.

Considering (6) and (13), we get the controller equations

$$u^*_{t+1} = \begin{cases} \min\{u_{\max}, u^*_t + \delta_t, \tilde{u}_{t+1}\}, & \text{if } \tilde{u}_{t+1} \geqslant u^*_t, \\ \max\{u_{\min}, u^*_t - \delta_t, \tilde{u}_{t+1}\}, & \text{if } \tilde{u}_{t+1} < u^*_t, \end{cases} \tag{16}$$

$$\begin{aligned} \tilde{u}_{t+1} = & \left(\widehat{W}_{0,t}(z^{-1}) + \alpha_t\right)^{-1} \\ & \times \left\{\tilde{y}_{t+\tau+1} + z^{\tau+1}\left(\widehat{E}_t(z^{-1}) - \widehat{H}_t(z^{-1})\right)\varepsilon_{t|t-1}(\widehat{\mathbf{c}}_{t-1})\right\}, \end{aligned} \tag{17}$$

where

$$\tilde{y}_{k+\tau+1} = \begin{cases} y^*_{k+\tau+1} + \alpha_k \tilde{u}^*_{k+1}, & \text{if } k = t, \\ y_{k+\tau+1|k} + \alpha_k \tilde{u}^*_{k+1}, & \text{if } k = t-1, t-2, \ldots, \end{cases} \tag{18}$$

$\alpha_t = q_t/\widehat{b}_{o,t}$; $\widehat{b}_{o,t}$ is the current estimate of b_0 in $B(z^{-1})$.

In case when there are no restrictions for the control values, control algorithm is defined only by (17), taking into account that $\tilde{y}_{k+\tau+1} = y^*_{k+\tau+1}$ for all k.

The current parameter estimates $\hat{\mathbf{c}}_t$ are obtained in the process of identification in the closed loop by applying a recursive algorithm (Kaminskas, 1982).

The block diagram of the above described self-tuning control system is given in Fig. 3.

Such is the framework of a predictor-based self-tuning control system for a common linear plant. Let's discuss special cases together with practical recommendations for managing them.

3. Special cases in control of linear plants

3.1. Plants with inner feedbacks. In case of a linear control plant with inner feedback, its operation may be defined by the following difference equations

$$y_t = W_0(z^{-1})v_{t-\tau} + H(z^{-1})\xi_t, \tag{19}$$

$$v_t = u_t + \mu_t, \qquad \mu_t = W_F(z^{-1})y_{t-\tau'}, \tag{20}$$

where

$$W_F = \frac{D(z^{-1})}{G(z^{-1})},$$

$$G(z^{-1}) = 1 + \sum_{j=1}^{n_g} g_j z^{-j}, \qquad D(z^{-1}) = \sum_{j=0}^{n_d} d_j z^{-j}, \tag{21}$$

is the transfer function of the feedback; $W_0(z^{-1})$ and $H(z^{-1})$ are transfer functions, defined by (2),(3); τ' is pure delay in the feedback.

Structural diagram of such a plant is given in Fig. 4.

Here we considered the presence of one equivalent feedback. In case there are several inner feedback chains, each of them can be presented and considered in a similar way.

Plants with inner feedbacks are met in power systems, in medical care systems (simulation of human cardiovascular system), etc. It is always possible, by applying adequate multiplication operations, to arrive at a common linear plant (Fig. 1), but in this case we shall have a greater amount of unknown parameters to be tuned. It is inefficient, especially if either the parameters of the

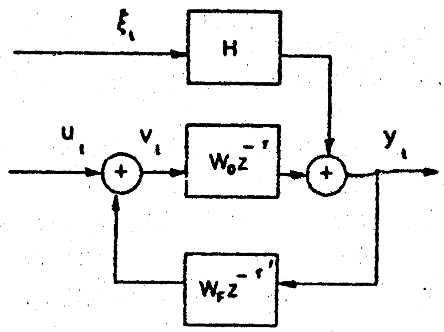

Fig. 4. Structural diagram of a linear plant with inner feedback.

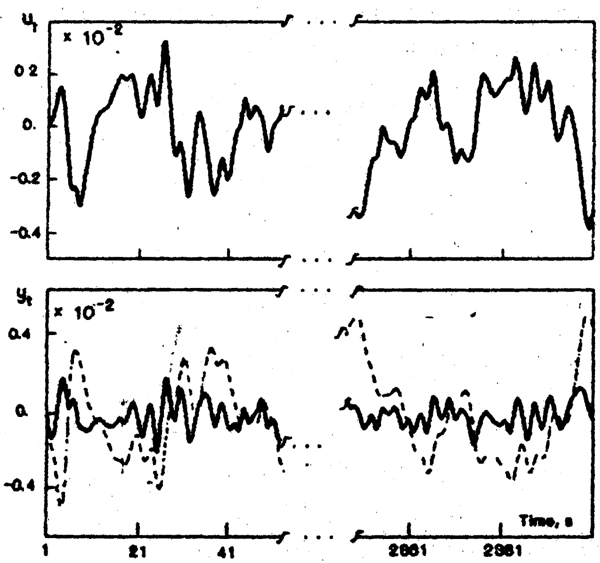

Fig. 5. Processes in the nuclear reactor under self-tuning control.

control channel or the feedback channel are known a priori, e.g. in power plants (Kaminskas *et al.*, 1990, 1991).

In case of a linear plant with inner feedbacks controller equations (16) and (18) remain unchanged, and instead of (17) we have

$$\begin{aligned}\tilde{u}_{t+1} =&(\widehat{W}_{0,t} + \alpha_t)^{-1}\{\tilde{y}_{t+\tau+1} + z^{\tau+1}(\widehat{E}_t(z^{-1}) \\ &- \widehat{H}_t(z^{-1}))\varepsilon_{t|t-1}(\widehat{\mathbf{c}}_{t-1}) - \widehat{W}_{o,t}(z^{-1})\widehat{W}_{F,t}(z^{-1})y_{t-\tau'}\}. \quad (22)\end{aligned}$$

Figure 5 illustrates the self-tuning control process for a nuclear power reactor in the stationary regime of operation. Reactor's operation can be defined by a linear model with inner feedbacks, the latter representing the effect of fuel and fuel-carrier variables on the fission properties of the reactor. Fig.5 presents the diagrams of the control signal (external reactivity) and the output signal (relative power deviations from a stationary level) at the beginning of the self-tuning control process and at the end of it. Diagram of uncontrolled output signal is presented for comparison (dashed line).

3.2. Plants with an unstable control signal channel. In case of a control plant (1) with an unstable control signal channel it is necessary to consider plant operation model with equal denominators of the transfer functions (2) and (3), i.e. with $R(z^{-1}) \equiv A(z^{-1})$. Then, instead of (15) and (17) we have the equations

$$y_{t+1|t}(\mathbf{c}) = P(z^{-1})^{-1}\Big\{z\big[P(z^{-1}) - A(z^{-1})\big]y_t + B(z^{-1})u_{t+1-\tau}\Big\} \quad (23)$$

and

$$\begin{aligned}\tilde{u}_{t+1} =&\big[\widehat{B}_t(z^{-1}) + \alpha_t\widehat{A}_t(z^{-1})\big]^{-1} \\ &\times \big[\widehat{A}_t(z^{-1})\tilde{y}_{t+\tau+1} - \widehat{L}_t(z^{-1})\varepsilon_{t|t-1}(\widehat{\mathbf{c}}_{t-1})\big]. \quad (24)\end{aligned}$$

3.3. Plants with a nonminimum-phase control signal channel. Let's discuss two possible ways of constructing predictor-based self-tuning control systems for nonminimum-phase plants.

3.3.1. Application of a generalized minimum variance control algorithm. Generalized minimum variance control algorithm is capable of coping with this problem by means of adequate choice of the coefficient q_t (Clarke, 1984). In this case the coefficient q_t might be considered as a root-locus parameter, and it can force the potentially unstable roots due to $B(z^{-1})$ migrate towards the roots of $A(z^{-1})$. If there are several possible q_t values (or a set of them), then an additional criterion can be applied in order to choose an appropriate q_t value, e.g.

$$I(q_t) = \sum_{i=1}^{n_s} |z_i(q_t)|^2 \rightarrow \min_{q_t}, \tag{25}$$

where $z_i(q_t)$ are the roots of the equation

$$S^*(z) = 0, \qquad S^*(z) = z^{n_s} S(z^{-1}), \tag{26}$$

$$S(z^{-1}) = B(z^{-1}) + \alpha_t A(z^{-1}) = \sum_{i=1}^{n_s} s_i z^{-i}, \quad n_s = \max\{n_a, n_b\}. \tag{27}$$

Sometimes a certain polynomial $Q(z^{-1})$ might be used instead of the coefficient q_t.

There might be cases when the minimum generalized variance controller is incapable of coping with the nonminimum-phase plant - no appropriate q_t (or $Q(z^{-1})$) values, or those values result in far too big losses in the control quality. In such case other methods might be applied, e.g. the factorization methods (Åström and Wittenmark, 1984).

3.3.2. Factorization methods. The polynomial $B(z^{-1})$ must be decomposed into two factors

$$B(z^{-1}) = B_+(z^{-1}) B_-(z^{-1}), \tag{28}$$

where

$$B_+(z^{-1}) = 1 + \sum_{i=0}^{n_b^+} b_i^+ z^{-i} \tag{29}$$

is a polynomial with all of its roots outside the unit circle;

$$B_-(z^{-1}) = \sum_{i=0}^{n} b_i^- z^{-i}, \qquad n = n_b - n_b^+ \tag{30}$$

is a polynomial with all of its roots in the unit circle or on its boundary.

In this case the polynomial $B(z^{-1})$ in the controller equations must be substituted by a polynomial

$$\widetilde{B}(z^{-1}) = B_{+}(z^{-1})\widetilde{B}_{-}(z^{-1}), \tag{31}$$

$$\widetilde{B}_{-}(z^{-1}) = \sum_{i=0}^{n} b_{n-i}^{-} z^{-i}. \tag{32}$$

4. Control of nonlinear plants. Several characteristic cases of applying predictor-based self-tuning control systems for nonlinear plants are considered.

4.1. Hammerstein-type plants with the nonlinear part in the form of a sum of monotonous nonlinearities. Such control plants are encountered when different groups of control devices are considered together with the control plant. Figure 6 presents the structural diagram of such a plant.

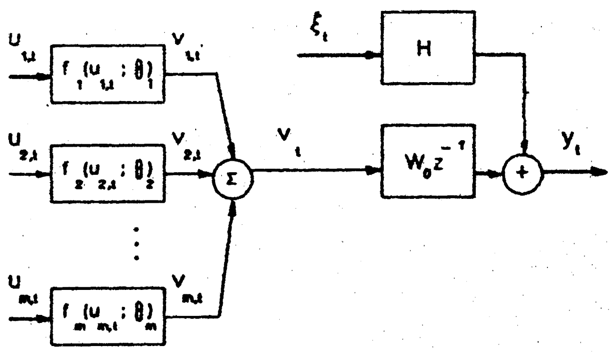

Fig. 6. Structural diagram of a nonlinear Hammerstein- type plant.

Nuclear power reactor may be an example of such a plant with monotonous nonlinearities representing different groups of control rods.

In this case synthesis of optimal control values can be accomplished in two stages. In the first stage only the linear part of the control plant is considered and an intermediate control value v^*_{t+1} is obtained by (16).

In the second stage the control signal, obtained in the first stage, is decomposed into a certain number of signals, taking into account the monotonous nonlinearities in the nonlinear section of the control plant. For this purpose values $\overline{v}^{*T}_{t+1} = (v^*_{1,t+1}, \ldots, v^*_{m,t+1})$ are determined by means of solving a conditional extremal problem

$$\overline{v}^*_{t+1}: \; Q^{\overline{v}}_t(\overline{v}_{t+1}) = \sum_{i=1}^{m} K_{i,t}\left(v_{i,t+1} - v^*_{i,t}\right)^2 \to \min_{\overline{v}_{t+1} \in \Omega_{\overline{v}}}, \tag{33}$$

$$\Omega_{\overline{v}} = \left\{\overline{v}: \; \sum_{i=1}^{m} v_{i,t+1} = v^*_{t+1}, \left|v_{i,t+1} - v^*_{i,t}\right| \leqslant \delta_{i,t}, v_i^- \leqslant v_{i,t+1} \leqslant v_i^+\right\}, \tag{34}$$

where $K_{i,t}$ is weight coefficient, indicating to the priority of the i-th control value. Then

$$u^*_{i,t+1} = f_i^{-1}(v^*_{i,t+1}; \theta_i), \quad i = \overline{1,m}. \tag{35}$$

The extremal problem (35) can be solved by means of the Lagrange-factor method.

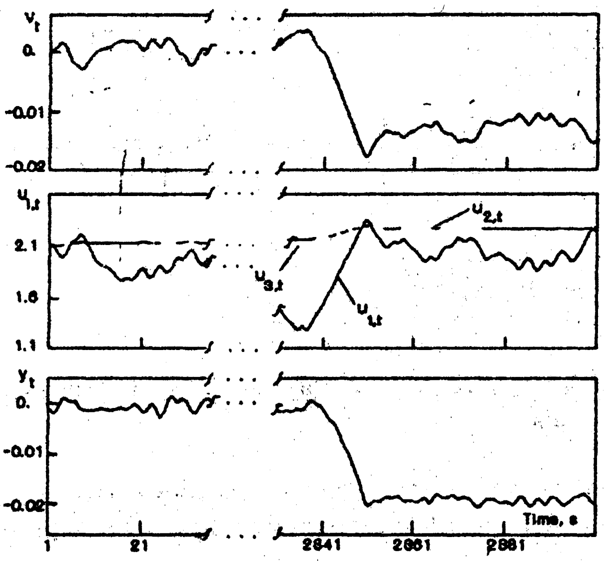

Fig. 7. Processes in the nuclear reactor under self-tuning control in the transition regime of operation.

Figure 7 illustrates the self-tuning control process for a nuclear power reactor in the transition regime of operation. Diagrams of intermediate control signal v_t, control signals $u_{i,t}$ $(i = 1, 2, 3)$ and output signal y_t are presented.

4.2. Wiener-Hammerstein-type plants with polynomial nonlinearities. Nonlinear dynamic systems are considered with an observed output signal y_t defined by

$$y_t = W_2(z^{-1}) f(v_t; \theta) + H(z^{-1})\xi_t, \tag{36}$$

$$v_t = W_1(z^{-1}) z^{-\tau} u_t, \tag{37}$$

where

$$f(v_t; \theta) = \sum_{i=1}^{n_\theta} \theta_i v_t^i \tag{38}$$

is a nonlinear characteristics of the static element with the parameters

$$\theta^T = (\theta_1, \theta_2, \ldots, \theta_{n_\theta}), \quad n_\theta \geqslant 2, \quad \theta_{n_\theta} \neq 0. \tag{39}$$

$$W_1(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})}, \quad W_2(z^{-1}) = \frac{D(z^{-1})}{G(z^{-1})} \tag{40}$$

are fractional-rational transfer functions in the form of (2), providing a unitary gain in the control signal channel.

The equations (36) – (40) specify so called Wiener - Hammerstein-type nonlinear stochastic plants with the nonlinear element standing between two linear dynamical parts (see Figure 8). Such a model, in particular, may be regarded as a good approximation of fuel combustion and steam condensation processes in power units of a thermal power plant (Kaminskas *et al.*, 1988, 1991). These processes are distinguished by their well-expressed nonlinearity (extremal characteristic) and inertness of input and output chains.

In particular cases, by removing the first or the second linear dynamical part, we can consider, respectively, Hammerstein-type or Wiener-type stochastic plants with polynomial nonlinearities.

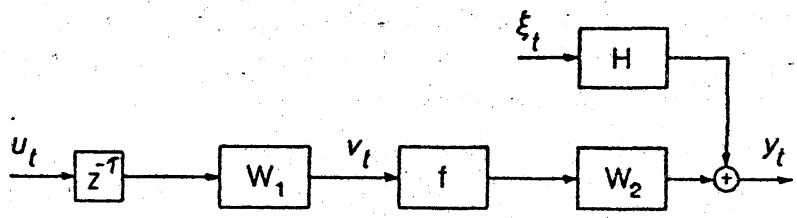

Fig. 8. Structural diagram of a Wiener-Hammerstein-type plant with polynomial nonlinearity.

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

$$\begin{aligned} y_{t+\tau+1}(\widehat{\mathbf{c}}_t) = & z^{\tau+1}[1-\widetilde{H}^{-1}(z^{-1})]y_t \\ & + \widetilde{H}^{-1}(z^{-1})W_2(z^{-1})f[W_1(z^{-1})z^{-\tau}u_t;\theta]. \end{aligned} \tag{41}$$

Applying the latter equation to control performance criterion equations (13), we find that the value $\widetilde{u}_{t+1}$ is obtained as a real root of $(2n_\theta - 1)$-th order equation.

In the case of $n_\theta = 2$ (extremal characteristic) the reference value y_t^* may be the current maximum point of the characteristic. The minimum generalized variance controller equations are (16), where $\widetilde{u}_{t+1}$ is any real root of

$$\begin{aligned} u_{t+1}^3 + \frac{3f'(s_t)}{2b_0\theta_2}u_{t+1}^2 + \frac{b_0^2 d_0\left\{2\theta_2\beta_t + d_0[f'(s_t)]^2\right\} + q_t}{2b_0^4 d_0^2\theta_2^2}u_{t+1} & \\ + \frac{b_0 d_0 f'(s_t)\beta_t - q_t\widehat{y}_t^*}{2b_0^4 d_0^2\theta_2^2} = 0, & \end{aligned} \tag{42}$$

where

$$\beta_t = d_0 f(s_t) + r_t - \delta_t - \widehat{y}_t^*, \tag{43}$$

$$\delta_t = z^{\tau+1}\left[\widehat{E}_t(z^{-1}) - \widehat{H}_t(z^{-1})\right]\varepsilon_{t|t-1}(\widehat{\mathbf{c}}_{t-1}), \tag{44}$$

$$s_t = z\left[\widehat{W}_1(z^{-1}) - b_0\right]u_{t-\tau}, \tag{45}$$

$$r_t = z\left[\widehat{W}_2(z^1) - d_0\right]f\left[\widehat{W}_1(z^1)u_{t-\tau};\theta\right], \tag{46}$$

$$f(s_t) = \theta_0 + \theta_1 s_t + \theta_2 s_t^2, \quad f'(s_t) = \theta_1 + 2\theta_2 s_t, \tag{47}$$

$$\widehat{y}_t^* = -\frac{\widehat{\theta}_1^2}{4\widehat{\theta}_2}. \tag{48}$$

Figure 9 demonstrates simulation results. The stages I and II represent self-tuning control process. At the initial stage parameter estimation errors are large, and at the second stage parameter estimates are close to their genuine values. The stage III illustrates the case of the self-tuning controller disconnected, i.e. the argument value u^* of the extremal characteristic is supplied to the input. Control efficiency degrades because there is no compensation of uncontrolled disturbances.

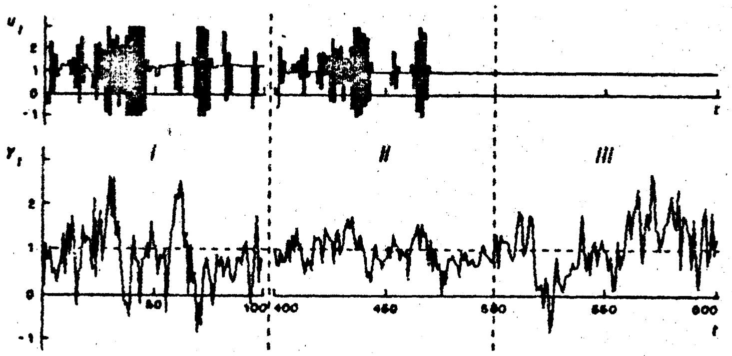

Fig. 9. Self-tuning control of Wiener-Hammerstein-type plant.

5. Conclusions. Design problems of predictor-based self-tuning minimum variance digital control systems are discussed. Practical issues of implementation of predictor-based self-tuning control systems for different types of control plants (linear plants with unstable and nonminimum-phase control channels, linear plants with inner feedbacks, nonlinear Hammerstein- and Wiener-Hammerstein-type plants) are considered.

Control algorithm synthesis is accomplished, taking into account amplitude and/or introduction rate restrictions for the control signals. The unknown parameters of the one-step predictor of the output signal are being estimated in the identification process in the closed loop. using recursive least squares algorithm.

Simulation results are given to illustrate the implementation of predictor-based self-tuning control systems for different control plants. Certain operation regimes of thermal neutron and fast breeder nuclear reactors, fuel combustion and steam condensation processes in the power units of thermal power plants are considered. Simulation results show that predictor-based self-tuning control systems are expedient for the digital control of different types of control plants, power plants among them. The presented self-tuning control scheme can also be applied in designing man-operator supervisory and training systems for corresponding power plants.

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