Polska Akademia Nauk • Instytut Badań Systemowych

AUTOMATYKA STEROWANIE ZARZĄDZANIE

Książka jubileuszowa
z okazji
70-lecia urodzin

PROFESORA KAZIMIERZA MAŃCZAKA

pod redakcją
Jakuba Gutenbauma

Polska Akademia Nauk • Instytut Badań Systemowych

AUTOMATYKA STEROWANIE ZARZĄDZANIE

**Książka jubileuszowa
z okazji
70-lecia urodzin**

PROFESORA KAZIMIERZA MAŃCZAKA

**pod redakcją
Jakuba Gutenbauma**

Warszawa 2002

Książka jubileuszowa z okazji
70-lecia urodzin
Profesora Kazimierza MAŃCZAKA

Redaktor
prof. dr hab. inż. Jakub Gutenbaum

Warszawa 2002

ISBN 83-85847-78-2

Wydawca: Instytut Badań Systemowych PAN
ul. Newelska 6 01-447 Warszawa
http://www.ibspan.waw.pl

Opracowanie składopisu: Anna Gostyńska, Jadwiga Hartman

Druk: KOMO-GRAF, Warszawa
nakład 200 egz., 34 ark. wyd., 31 ark. druk.

ADAPTIVE SYSTEMS WITH CURRENT IDENTIFICATION – WEAK POINTS AND IMPROVING MODIFICATIONS

Ryszard Gessing

Politechnika Śląska, Instytut Automatyki
ul. Akademicka 16, 44-101 Gliwice, <gessing@gliwice.edu.pl>

Abstract: *It is noted that in adaptive control systems excited by a disturbance, the commonly used estimation algorithms based on current measurements of the plant input and output usually give unsatisfactory results. It is shown that additional measurements, especially of the additive disturbance radically improve the accuracy of the estimates. In the latter case the estimation of the parameters of the control channel and of the disturbance model may be performed separately with different values of a forgetting factor. The original proposal of system excitation by means of intentional, additive disturbance compensated by the control, measured and used in estimation, is given. In this case the exciting oscillations almost do not appear in the output. The described observations are confirmed by the results of simulations.*

Keywords: *adaptive systems, estimation, system excitation.*

1. Introduction

The adaptive control systems should work under varying plant parameters and at the presence of disturbances, whose influence on the plant output should be compensated by control. The estimation of these parameters plays an essential role in such systems.

There is a large number of possible types of controllers and recursive estimation algorithms, which may be used as a basis of adaptive systems. They should be designed to work in a wide spectrum of conditions defined by the behaviour of disturbances, set point values and system parameters. Especially the theory of self-tuning control is quite well established (Åström et al. 1989, Isermann et al. 1992, Kosut et al. 1987, Ljung et al. 1983). However, theoretical results concerning e.g. stability, optimality, order estimation, time-varying parameters and consistency of plant parameter estimates are only valid under special conditions and for selected groups of self-tuners. Widespread assumptions are constant parameters and standard recursive estimation methods without data forgetting. In practice, parameters do change and the forgetting factor is used in the estimation algorithm.

An essential question for estimation algorithms is to ensure a sufficiently rich excitation of the system. It is expressed in the so called persistent excitation (PE) condition. In the closed loop (CL) system the PE condition may be violated even in the case of sufficiently rich exciting noises, which may produce problems with identifiability and convergence (Gustavsson et al. 1977).

In the present paper the attention is focused on the problems related to on-line parameter estimation. It is noted that the commonly used estimation algorithms basing on current measurements of the plant input u and output y usually give unsatisfactory results. This is caused by the fact that in the system, in which the influence of the disturbance v on the output y is compensated by the control u, the measured pair (u, y) contains poor information about interesting parameters.

Therefore, if possible, it is reasonable to perform some additional measurements, especially of the disturbance v, to increase the amount of information about the estimated parameters. It is shown that the use of additional measurement of the disturbance v radically improves the accuracy of the estimates and the quality of control.

For a weakly excited system, the original way of excitation is proposed by means of intentional disturbance v, generated outside of the system and added to the plant output. This kind of excitation gives negligible output oscillations since the influence v on y is compensated by the control.

The contribution of the paper is partly in showing that additional measurements, especially of the disturbance v improve radically accuracy of the varying parameter estimates and partly in the proposal of the system excitation by means of intentional disturbance generated outside of the system, added to the plant output and compensated by the control.

2. Commonly used approach

The model of the plant and disturbance mostly used for description and research of adaptive control systems takes the form

$$A(z^{-1})y(i) = B(z^{-1})u(i-d) + C(z^{-1})e(i) \tag{1}$$

where $u(i)$ and $y(i)$ are the plant input and output signals, $e(i)$ denotes a Gaussian white noise with $N(0,\sigma^2), i = 0, 1, 2, ...$ denotes the discrete time, d - time of delay, $z^{-1}y(i) = y(i-1)$, and $A(z^{-1}), B(z^{-1}), C(z^{-1})$ are the appropriate polynomials.

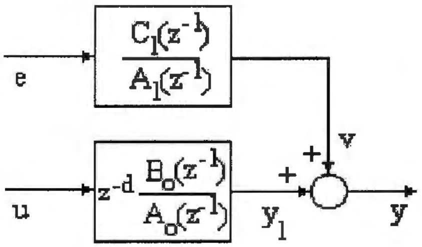

Fig. 1. The model of the plant and disturbance.

It is worthwhile to remind that the equation (1) describes also the dependence between the output y and input u, with accounting the disturbance, for the model shown in Fig. 1. The latter model is described by

$$y(i) = z^{-d}\frac{B_0(z^{-1})}{A_0(z^{-1})}u(i) + v(i) \tag{2}$$

where the first term on the right hand side of (2) describes the control channel, and $v(i)$ is the disturbance described by

$$v(i) = \frac{C_1(z^{-1})}{A_1(z^{-1})}\, e(i). \tag{3}$$

The formula (3) determines the properties of the stochastic process $v(i)$ (Åström et al. 1989).

In the commonly used approach, to estimate varying parameters, the current measurements of the signals u and y are utilised in an appropriate estimation algorithm. One of the most frequently used is the recursive extended least squares (RELS) estimation algorithm in the weighted version in which the forgetting factor λ is used. The factor λ makes it possible to take into account new measurements and to forget the old ones.

3. Weak points of the approach

The weakest point of the described approach is performing the parameter estimation on the basis of only the measurements of input u and output y and under an ideal disturbance v described by (3). To justify this view, note that the goal of the adaptive control system is to compensate the influence of the disturbance v on the output y, under varying plant parameters. It means, that for the zero set point w, in the ideal case $y \approx w = 0$, while for the constant set point $y \approx w = const$. Then, if the system works well, then the pair (u, y) contains no information about the plant parameters.

Thus, generally, when the signals u, y are used in estimation there arises the contradiction between the two goals: disturbance compensation and parameter estimation. The adaptive control system should realise both these goals. The contradiction means that a better realisation of one from them means a worse realisation of the other. Of course, in the case of constant plant parameters all these observations are less essential. For this case there exist many papers describing some good properties of the algorithms analysed therein, working in some idealised conditions.

However, the remarks become essential in the case of varying plant parameters, especially when the disturbance v is of the ARMA type (i.e. if in the model (1) the polynomial $C(z^{-1})$ appears). It is known that the appearance of this kind of disturbance v increases the difficultty of parameter estimation. In fact, it can be concluded from many simulation experiments that the RELS algorithm in the weighted version can work then only for λ very close to 1, e.g. $\lambda = 0.98$. It means that the difficulties appear when the parameters are varying in time, since for such a λ their variations cannot be tracked. On the other hand, for smaller λ, say $\lambda = 0.95 - 0.9$ the bursting phenomena appear (non stable periods), when the parameters are varying.

Another known consequence of the choice of the pair (u, y) for use in estimation is that for the set point $w = 0$ the regulator algorithm may determine some linear dependence between the measurements of u and y. The consequence is the singularity of appropriate measurement matrix and the collapse of the RELS algorithm. It can be shown that similar properties appear also in the case of $w \neq 0$ (Gessing 1996). The result is that the plant parameters cannot be estimated in the CL system. The resulting difficulty is avoided by showing that, though the plant parameters cannot be then estimated, the regulator parameters can, and whole the system can work, though only in some ideal conditions.

4. The meaning of disturbance measurement

It is worthwhile to realise that the use of the pair (u, y) in estimation is justified only in two cases. First, if the signal v represents the error of the measuring device; second, if v represents the disturbance, but there is no possibility of performing additional measurements.

In the first case the variance of the measurement error v is rather small, which causes that the estimate errors are also small. This is the classical problem of parameter estimation with inaccurate measurements containing the measurement error v. In the second case, the pair (u, y) must be used in estimation since no additional measurements are available. The signal v has then a greater variance than in the first case. It should be noted that from the calculation point of view, the problem of parameter estimation in the second case is the same as in the first one. However, since the variance of v is greater, the calculated estimates are very sensitive to non fulfilment of the assumptions concerning v. In practice, these assumptions are rather rarely fulfilled, which causes that such an estimation does not work correctly.

Therefore, it is very important to have the possibility of performing some additional measurements, which may be utilised in parameter estimation. The crucial role is played by the additional measurement of the disturbance v. Really, if the parameter estimation of the model shown in Fig. 1 is performed using the current measurements of u, y and v, then the signal $y_1 = y - v$ may be determined and the two mutually independent estimation problems may be solved, separately. The first problem – estimation 1 – concerns the control channel parameters and the second – estimation 2 – the disturbance model parameters. The estimation 1 problem may be solved using the RLS algorithm and the pair (u, y_1), which radically improves the estimation conditions. The signals u, y_1 have then a deterministic character and are directly related to the control channel parameters.

Additionally, under existence of sufficiently exciting disturbance v, compensated by control (i.e. when $y \approx w$), the estimation 1 may be performed without variations of the output y from its ideal values.

Further advantage is the possibility of using significantly smaller values of the forgetting factor λ (e.g. $\lambda = 0.9$) for the estimation 1 algorithm, since information contained in the pair (u, y_1) is significantly richer than that in the pair (u, y). Owing to this, it is possible to perform estimation for significantly faster parameter variations. Another advantage is insensitivity of the estimation 1 algorithm to the non ideal disturbances.

In the estimation 2 problem the parameters of the disturbance v are estimated using the RELS algorithm and the measurement of v. Since information about these parameters, contained only in v, is poor (the realisations of e are not known), then λ should be close to 1 (e.g.$\lambda = 0.99$); this means that only a stationary model of the disturbance may be estimated. Additionally, estimation 2 is very sensitive to non ideal disturbances, not fulfilling appropriate assumptions.

It is worthwhile to note that realisation of estimation 2 is not needed for implementation of some adaptive control basing on a suboptimal control algorithm. It is needed only when in the adaptive system some stochastic optimal control algorithm is realised. Therefore, it is important that in the proposed approach the estimation 1 problem, which must usually be performed in the adaptive control systems, is better conditioned.

Finally, note that the additional measurement of the disturbance v and the use of the pair (u, y_1), $y_1 = y - v$ in the CL estimation removes the linear dependence between u and y_1. Owing to this it is possible to perform the estimation of the plant parameters in the CL system.

4.1. Example

Consider the model of the type (1) with

$$\begin{aligned} A(z^{-1}) &= 1-1.6z^{-1}+0.8z^{-2} \\ B(z^{-1}) &= k(3-1.5z^{-1}) \;, \; d=1 \\ C(z^{-1}) &= 1-0.4z^{-1}+0.4z^{-2} \end{aligned} \tag{4}$$

i.e. $a_1 = -1.6$, $a_2 = 0.8$, $b_0 = 3$, $b_1 = -1.5$, $c_1 = -0.4$, $c_2 = 0.4$, $w(t) = 1$ is the set point and k is a coefficient, which will be varied at the time of simulation in accordance with the formula $k(i) = 1 + 0.9sin(0.01i)$. Thus, the plant gain is varied from the minimal value of 0.75 to the maximal value of 14.25. The Gaussian white noise $e(i)$ has the parameters $N(0, \sigma^2 = 0.01)$.

The minimum variance controller algorithm, which minimises the performance index

$$I = E[y(i+d) - w(i)]^2 \tag{5}$$

(where E denotes the mean and $w(i)$ - the set point) takes the form (Gessing and Błachuta, 1996)

$$\begin{aligned} &k(b_0 + b_1 z^{-1})u(i) = (1 + c_1 z^{-1} + c_2 z^{-2})w(i) + \\ &+[(a_1 - c_1) + (a_2 - c_2)z^{-1}]y(i). \end{aligned} \tag{6}$$

In the adaptive control system studied below the algorithm (6) is used, in which in the place of the coefficients their appropriate estimates calculated with the RELS algorithm are used.

The simulations of this system were performed with using SIMULINK ver 1.3c package. Many experiments were performed and the results of four of them are shown in Figs 2-5. Two different sets of measurements were used in the simulations.

4.1.1. Measurements of u and y

In the case when only the measurements of u and y were available, the estimation of all the parameters a_1, a_2, kb_0, kb_1, c_1, c_2 was performed with using the RELS algorithm. Two different values of the forgetting factor λ were used, and the results are shown in Fig. 2 and 3.

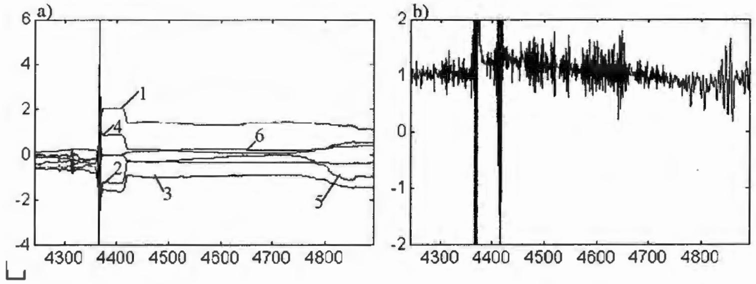

Fig. 2. a) Parameter estimates for $\lambda = 0.99$, $1 - kb_0, 2 - kb_1, 3 - a_1, 4 - a_2, 5 - c_1, 6 - c_2$; b)Output (measured u, y).

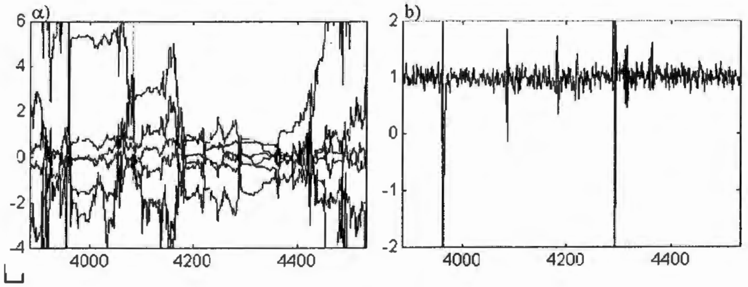

Fig. 3. a) Parameter estimates for $\lambda = 0.9$; b) Output (measured u, y).

The results of simulations shown in Fig. 2 concern the case of $\lambda = 0.99$. It is seen that the estimates are not related with the true values of the parameters, which results from the fact that for the assumed λ the varying parameters cannot be tracked. The result is that in the controlled output y there appear bursts at the time of which the output y attains very high values. After a successive burst, some improvement of the parameter estimates usually appears.

The results of simulations shown in Fig. 3 concern the case of $\lambda = 0.9$. The plots of the parameter estimates are strongly rugged and there is no relation between them and the true values of the parameters. This results from the fact that for $\lambda = 0.9$ the period of averaging is too short and the instantaneous, unknown values of v disturb the estimation significantly. In the output plot the bursts appear even more frequently than in Fig. 2, but they are shorter. It means that also the appropriate regulator parameter estimates are not well determined.

It can be concluded from many simulations performed for the considered example that on the basis of the measurements (u, y), using RELS algorithm and different values of λ, it is not possible to obtain a satisfactory control without bursts.

4.1.2. Measurements of u, y and v

In Fig. 4 and 5 the results of simulations in the case when the disturbance v is also measured are shown, i.e. the parameter estimation is performed using the triplet (u, y, v). The parameters a_1, a_2, kb_0, kb_1 are estimated using the RLS algorithm with the pair (u, y_1) , $y_1 = y - v$, and the parameters c_1, c_2 – using the RELS algorithm and v together with the estimates of a_1 and a_2 taken from the RLS algorithm.

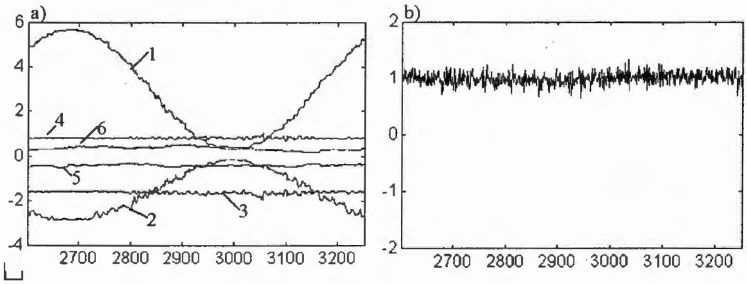

Fig. 4. a) Parameter estimates for $\lambda_1 = 0.9, \lambda_2 = 0.99$, $1 - kb_0, 2 - kb_1, 3 - a_1, 4 - a_2, 5 - c_1, 6 - c_2$; b) Output (measured u, y, v).

In Fig. 4 the results of simulations are given for the case when RLS and RELS estimation is performed with $\lambda_1 = 0.9$ and $\lambda_2 = 0.99$, respectively. It is seen that the estimates are very close to the true parameter values and some insignificant ruggedness appears in a_1, a_2, kb_0, kb_1 in the periods of faster variations of the coefficient k. The plot of the output y is very close to the optimal values of the minimum variance control (i.e. $y(i) = 1 + e(i)$).

In Fig. 5 the results of simulations are given for the case when both the RLS and RELS estimations are performed with $\lambda_1 = \lambda_2 = 0.9$.

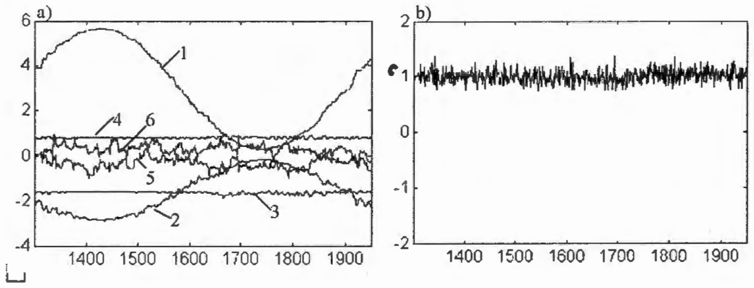

Fig. 5. a) Parameter estimates for $\lambda_1 = \lambda_2 = 0.9$, $1 - kb_0, 2 - kb_1, 3 - a_1, 4 - a_2, 5 - c_1, 6 - c_2$; b) Output (measured u, y, v).

It is seen that the plots of the estimates a_1, a_2, kb_0, kb_1 are very close to those shown in Fig. 4, while the estimates of c_1, c_2 have now some stronger ruggedness. The output is some - what worse than that shown in Fig. 4.

5. Excitation by intentional disturbance

Consider the adaptive system in which the set point $w = const$ and the influence of the disturbance v on the output y is compensated by the CL control u. Then we have $y \approx w = const$ and the estimation basing on the measurements (u, y) is badly conditioned. For the same disturbance v the estimation using the triple (u, y, v), i.e. basing on (u, y_1), may be well conditioned. Thus it is seen that *for estimation performed in a CL system the problem conditioning is dependent not only on system excitation but also on the measurements creating the available information.*

In connection with this there arises the idea of adaptive system excitation by means of intentional disturbance v generated outside of the system, added to the plant output and compensated by the CL system control u, as shown in Fig.6. For the plant with $2n$ identified parameters, the intentional disturbance may take the form

$$v(t) = Asin(\omega_1 t) + Asin(\omega_2 t) + ... + Asin(\omega_n t) \tag{7}$$

where, say $A = (0.2 - 0.5)w$ and the frequencies $\omega_1, \omega_2, ..., \omega_n$ are chosen so that they are sufficiently compensated by the CL control and are as high as possible ($\max_i \omega_i$ is close to the bandwidth frequency). The efficiency of the compensation may be increased by applying some appropriate correctors, as it will be shown in the following example.

It should be stressed that in adaptive systems only sufficiently slowly varying plant parameters may be estimated. However, there is also a dependence: the higher the frequencies of the disturbance (7) - the faster the variations of the parameters that may be estimated.

One should realise that implementation of the proposed excitation idea is connected with appropriate construction changes of the plant. This is the result of the fact that usually power is related with the output y and the additive disturbance v. For different kinds of plants very interesting construction proposals are possible, but this goes beyond the scope of the paper. Of course, implementation of this idea is justified only when there is a real need for adaptive control system working without oscillations in the output y.

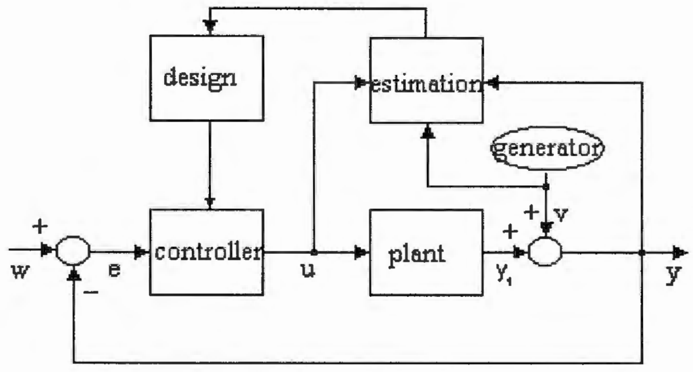

Fig. 6. Adaptive system with intentional excitation.

5.1. Example

Consider the adaptive system shown in Fig. 6, in which the plant is composed of a sampler, zero-order hold and a continuous-time (CT) plant described by the transfer function (TF)

$$G(s) = \frac{k}{(T_1 s + 1)(T_2 s + 1)} \tag{8}$$

where $T_1 = 1$, $T_2 = 0.5$ and the gain k will be varied.

5.1.1. Four Parameters Estimated

First, during the simulations, it is assumed that all the parameters of the CT plant's $G(s)$ (8) are unknown, while the sampling period $h = 0.1$ is known. The four parameters b_1, b_2, a_1, a_2 of the corresponding discrete-time (DT) plant, described by TF

$$H(z) = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2} \tag{9}$$

are estimated using the RLS algorithm with forgetting factor $\lambda = 0.9$ and measurements of $u(ih)$, $y(ih)$, $v(ih)$. The intentional disturbance $v(t)$ has two sinusoids

$$v(t) = 0.5sin(1.25t) + 0.5sin(2.5t). \tag{10}$$

To compensate some constant and sinusoidal (with $\omega = 2.5$) excitations in steady state, the internal model corrector described by the TF

$$C(z) = \frac{1}{z^3 - pz^2 + pz - 1} = \frac{U(z)}{X(z)} \tag{11}$$

is applied, for $\omega = 2.5$, $h = 0.1$ (Francis et al., 1976); here $p = 1 + 2\cos(\omega h)$, while $U(z) = \mathcal{Z}[u(ih)]$ and $X(z) = \mathcal{Z}[x(ih)]$; u, x are output and input of the corrector (output u of the corrector determines the input of the DT plant (9)).

The controller is designed using LQ technique for the augmented plant described by the TF

$$C(z)H(z) = \frac{Y_1(z)}{X(z)}. \tag{12}$$

For our example the augmented plant (12) results from multiplying (9) by (11) and takes the form

$$\frac{b_1 z + b_2}{z^5 + \bar{a}_1 z^4 + \bar{a}_2 z^3 + \bar{a}_3 z^2 + \bar{a}_4 z + \bar{a}_5} = \frac{Y_1(z)}{X(z)} \tag{13}$$

where the coefficients $\bar{a}_i$ result from this multiplication and $Y_1(z) = \mathcal{Z}[y_1(ih)]$. To formulate the LQ problem the state coordinates are determined by $x_1(ih) = e(ih+3h)$, $x_2(ih) = e(ih+2h)$, $x_3(ih) = e(ih+h)$, $x_4(ih) = e(ih)$, $x_5(ih) = e(ih-h) + \delta_1 x(ih-h)$, $e(ih) = -y_1(ih)$, $\delta_1 = -b_2/\bar{a}_5$; the state equations describing the augmented plant (13) result from this determination. Note that at the time of controller design we substitute $w(ih) = 0$ and $v(ih) = 0$.

The performance index used for the controller design takes the form

$$I = \sum_{i=0}^{N} \{e'(ih)Qe(ih) + r[x(ih)]^2\} \tag{14}$$

where $N \to \infty$, $Q = f'f$, $f = [0, 1, -1.9001, 0.9048, 0]$, $r = 0.001$, which assures partial pole placement of the CL system.

Finally, the controller with the internal model corrector (11) included is described by

$$\frac{U(z)}{E(z)} = \frac{k_1 z^4 + k_2 z^3 + k_3 z^2 + k_4 z + k_5}{(z + k_5\delta_1)(z^3 - pz^2 + pz - 1)} \tag{15}$$

where k_j, $j = 1, 2, 3, 4, 5$ result from the use of the MATLAB function *dlqr*.

The results of simulations for the set point $w(t) = sin(0.025t)$ and the periodical saw-toothed gain ($k(t) = 1 + 0.9(1 - t/(200\pi))$, for 0 □ t □ 200π, $k(t + 200\pi) = k(t)$) are shown in Fig. 7. It is seen that the estimates of b_1, b_2 track with some oscillations the variations of $k(t)$; the values of estimates of b_1, b_2 are very small in comparison with those of a_1, a_2. The output y tracks the sinusoidal set point w, but it has some oscillations (with $\omega = 1.25$), which are greater when the gain k is smaller; in the periods of small k the compensation action of the control u is very strong – but insufficient, which results from the cost of control; smaller r would increase the gain of the controller and would decrease these oscillations. It may be noted that, due to the resonant corrector designed for $\omega = 2.5$ the oscillations with this frequency disappear in the output y. It is seen that after 19-th time of the step-wise increase of the gain k the system becomes non stable for a short period of time, only.

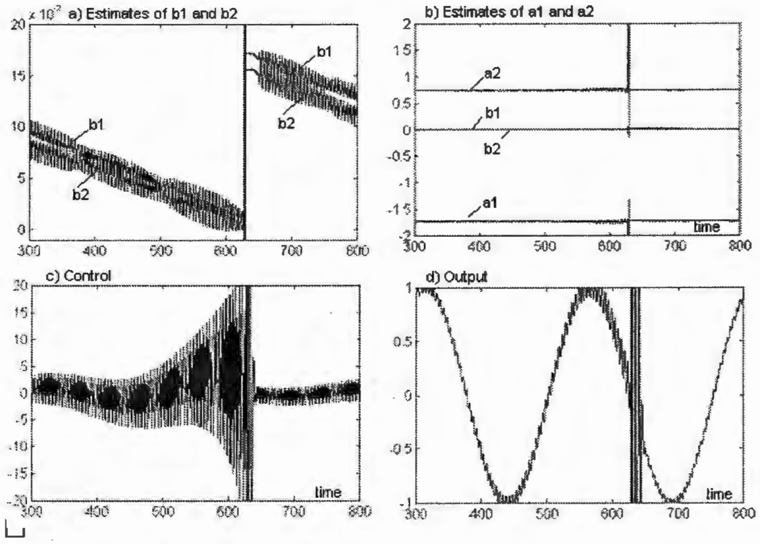

Fig. 7. Results of simulations for the case of four estimated parameters.

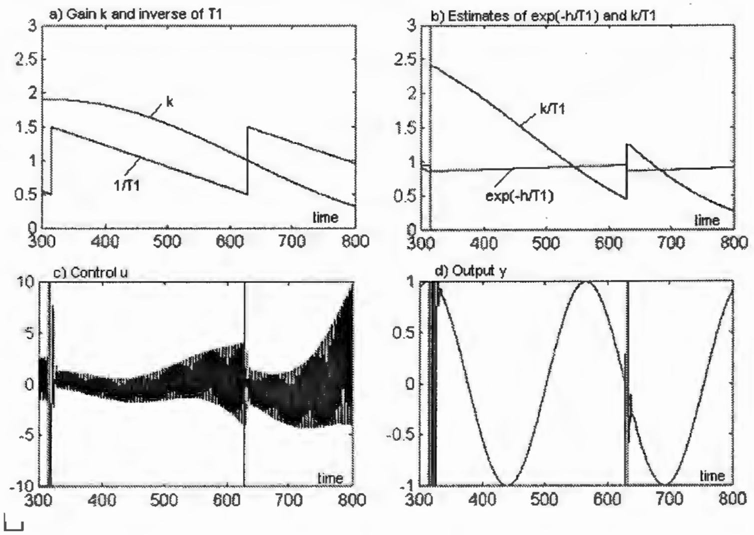

Fig. 8. Results of simulations for the case of two estimated parameters.

Note that till now the information about the parameters T_1, T_2 was not used in the estimation. When it is used, the estimation of only two parameters of $H(z)$ is needed and v may contain only one sinusoid. In fact, we obtain from the relation between the poles of TF-s (8) and (9)

$$y_1(ih) - (e^{s_1 h} + e^{s_2 h}) y_1(ih - h) + e^{(s_1+s_2)h} y_1(ih - 2h) =$$

$$= u(ih - h) b_1 + u(ih - 2h) b_2 \tag{16}$$

where $s_1 = 1/T_1$ and $s_2 = 1/T_2$ are known. Thus, the left hand side of (16) is known from measurements of $y_1(ih)$ and only two unknown coefficients b_1 and b_2 appear, which may be estimated using (16) and the measurements $y_1(ih), u(ih)$. Since only one sinusoid appears in v then an appropriate resonant corrector may efficiently reduce the oscillations of the output, caused by the disturbance. This will be shown in the following.

5.1.2. Two Parameters Estimated

Consider the same system with $G(s)$ described by (8), but now two parameters are varying, namely the gain $k(t) = 1 + 0.9sin(0.005t)$ and the inverse of time constant $1/T_1(t) = 1 + 0.5(1 - t/(100\pi))$ for 0 □ t □ 100π and $1/T_1(t + 100\pi) = 1/T_1(t)$; $T_2 = 0.5$, $w(t) = sin(0.025t)$. Now, the information about the parameter T_2 will be used in estimation. Since $h = 0.1$ is relatively small in relation to T_1 and T_2, then the approximation of $H(z)$ (9) described in (Gessing 1999) may be used. In our case the approximation takes the form

$$y_1(ih) = \frac{k}{T_1} h^2 \frac{z+1}{(z - e^{-0.2})(z - e^{-h/T_1})} u(ih) \tag{17}$$

or

$$y_1(ih) - e^{-0.2} y_1(ih - h) =$$

$$= [y_1(ih - h) - e^{-0.2} y_1(ih - 2h)] e^{-h/T_1} +$$

$$+ h^2 [u(ih - h) + u(ih - 2h)] \frac{k}{T_1} \tag{18}$$

In (22) only two unknown parameters e^{-h/T_1} and k/T_1 appear linearly; they may be estimated using RLS algorithm applied to (22) and measurements $y_1(ih)$, $u(ih)$. Only one sinusoid may be applied in v for excitation. The coefficients of (11) result from $b_1 = b_2 = (h^2(k/T_1)$, $a_1 = -(e^{-0.2} + e^{-h/T_1})$, $a_2 = e^{-0.2}e^{-h/T_1}$.

The results of simulations are shown in Fig. 8. It is seen that even for two varying parameters the results of simulations are significantly better than those shown in Fig. 7, though only the approximate description (17) was used. The oscillations of the output caused by the disturbance v disappear. Similarly as previously, the step-wise change of the time constant T_1 causes the appearance of a short non stable period.

6. Conclusions

In the commonly studies adaptive control systems the plant parameter estimation is performed using measurements of input u and output y of the plant. The system excitation comes from the disturbance v, the influence of which should be compensated by the CL control. This kind of systems cannot work well, especially in the case of varying plant parameters. The output y in this case does not contain information about the parameters of the control channel. The information needed appears after a deviation of the output y from its optimal value. In the case of disturbance correlated in time, the RELS algorithm with forgetting factor λ close to 1 may be applied. The varying parameters cannot be estimated and the bursts (non stable periods) appear, usually not accepted by the users.

When only the measurements (u, y) are used in estimation, there arises a contradiction between the two goals: disturbance compensation and parameter estimation. The contradiction means that better realisation of one of them means worse realisation of the other.

The performance of an adaptive control system may be improved radically if the additive disturbance v is also measured and the triplet (u, y, v) is used in the estimation algorithm. In this case the parameters of the control channel and of the disturbance model may be estimated, separately, using different values of λ. Owing to this some significantly faster parameter variations of the control channel may be estimated successfully.

The pair (u, y_1), $y_1 = y - v$, has significantly more information about the parameters of the control channel than the pair (u, y) (for the system excited by the disturbance v). For instance, the persistently exciting (PE) condition (Åstr—"om et.al., 1989) can be fulfilled for the pair (u, y_1) and not fulfilled for the pair (u, y). This means that not only the system excitation but also the measurements creating the available information play an essential role in the fulfilment of the PE condition.

When the triple (u, y, v) is used in estimation then both goals: estimation and compensation may be realised successfully. In this case the system may be well excited even in the case when $y \approx w = const.$, since then the signal $y_1 = y - v$ contains oscillations compensating the noise v. In this case the contradiction mentioned above disappears.

The idea of the adaptive system with intentional, additive disturbance, presented in the paper, makes it possible to improve a non sufficient excitation of the system. The intentional disturbance should be appropriately chosen, so that it well excites the system and its influence on y is compensated by the CL control.

The sinusoidal components of the intentional disturbance with possible high frequencies excite the system; lying in the working frequency band of the CL system they are compensated by the CL control. The resonant correctors improve the compensation.

The use of the known parameters of the CT plant decreases the number of the estimated parameters and the number of used sinusoids in the exciting disturbance, which may significantly improve the quality of estimation and control.

One may suppose that some additional measurements of other appropriate signals may also improve the system performance. In this case the estimation of several groups of parameters for lower order models may be calculated, separately.

7. ACKNOWLEDGEMENT

The paper was partially supported by the State Committee for Scientific Research (KBN).

References

Åström K.J., Wittenmark B. (1989) *Adaptive Control.* Addison-Wesley.

Francis B.A., Wonham W.M. (1976) The Internal Model Principle of Control Theory. *Automatica*, **12**, 457-465.

Gessing R.(1996) Measurements and Estimation in Adaptive Control Systems. In *Proceedings of the XIII-th IFAC Word Congress*, San Francisco, 1-5 July, **K**, 103-108.

Gessing R., M. Błachuta (1996) Set Point and Identifiability in the Closed Loop with Minimum Variance Controller. *Control Engineering Practice* **4**, 5, 665-670.

Gessing R. (1999) Word Length of Pulse Transfer Function for Small Sampling Periods. *IEEE Trans. Autom. Control*, **44**, 9, 1760-1764.

Gustavsson L., Ljung L., Söderström T. (1977)Identification of processes in closed-loop identifiability and accuracy aspects. *Automatica*, **13**, 59-75.

Isermann R.K., Lachmann H., Matko D.(1992) *Adaptive Control Systems.* Prentice Hall

Kosut R.L, Anderson B.D.O., Mareels I.M.(1987) Stability theory for adaptive systems: method of averaging and persistency of excitation. *IEEE trans. Autom. Control*, **32**, 26.

Ljung L., Söderström T. (1983) *Theory and Practice of Recursive Identification.* MIT Press.

ISBN 83-85847-78-2