ALGORITHMS FOR SOLVING THE JOINT IDENTIFICATION AND CONTROL PROBLEM FOR ADAPTIVE SYSTEMS

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Abstract. When designing adaptive control systems with an identifier (ASI), one faces challenges due to the statistical dependence of control signals on input disturbances. This dependence is stronger for better-trained systems. (Here, training means the process of model building.) Different methods and algorithms are used to identify and control a given plant by finding a trade-off between system training and control. The identification and control algorithms proposed in this paper solve both identification and disturbance control problems for a linear plant. In the case of random input disturbances, the parameter estimates yielded by these algorithms are shown to converge in mean square to the plant's parameters under the following conditions: the correlation matrix of the input disturbances is nonsingular; the ratio of the control parameter estimate to its real value is less than 2 by magnitude, and this estimate has the same sign as the control parameter. The algorithms can be used to track the time-varying parameters of the plant. The application of these algorithms generates a disturbance control system of a new kind. This system has several distinctive features: the control signal is not transmitted to the identifier; the control parameter is not directly estimated by the identifier (its value affects the estimates of the system parameters at the input disturbances); and the controller produces the control signal only based on the estimates of the system parameters at the input disturbances.

Keywords: identification, adaptive algorithm, adaptive control system with identifier (ASI), disturbance control, stabilization, the degeneracy problem of a correlation matrix.

INTRODUCTION

Efficient process control is a fundamental aspect of increasing the profitability of industrial enterprises, strengthening their competitiveness, and ensuring high-quality products. When addressing the above issues, the key role is played by the development and implementation of industrial process models based on identification theory [1, 2]. These models have demonstrated high efficiency in various industrial sectors, such as power supply, mechanical engineering, metallurgy, petrochemicals, and fertilizer production, as well as in similar problems in biology, physiology, and medicine.

A new kind of control systems, known as adaptive systems with an identifier (ASI) [1], was developed to control technical systems. The principle of predictive control was implemented within ASI. This approach optimizes current industrial processes and, moreover, considers future changes in the system's operating conditions, significantly enhancing its adaptive capabilities and stability under exogenous disturbances.

Modern ASIs, with possible application of knowledge-based intelligent identification algorithms, represent a powerful tool for solving a wide range of tasks, from the stabilization of industrial processes to their comprehensive optimization according to various criteria (maximum productivity, minimum costs, reduced resource consumption, etc.). ASIs operate in real time, integrating a predictive model of the plant; this model is based on experimental data and is continuously updated during operation. Its accuracy directly affects control efficiency.

Various methods and algorithms are used to build models: from simple one-step methods to complex ones based on artificial intelligence (AI). One-step algorithms were analyzed in detail in [3], including their application in pipe rolling accuracy control systems.

To identify complex nonlinear dynamic systems, a new-generation identification algorithm was proposed in [4, 5]. Rather than building a single approximating model of a real process for the entire range of observations, this algorithm creates a new model at each step, using data from the process archive and, where possible, expert knowledge from a knowledge base. The data selection algorithm, formalized through a certain predicate, was called the associative search algorithm. (Note that the corresponding approach has proven effective in various industries, such as fertilizer production, petrochemicals, and power supply [2, 4–7].)

However, certain challenges arise when applying the aforementioned identification algorithms to stabilization systems (actually, the majority of industrial plants). The challenges stem from the fact that, in the conventional design of adaptive identification systems, control is statistically dependent on input disturbances. This dependence is stronger for better-trained systems. (Here, training means the process of model building.) According to [3], for a linear plant, the convergence rate of the algorithm slows down significantly; under a certain ratio of the estimates of the plant's parameters to their real values, the training process may even halt. Thus, in stabilization systems with an identifier, there is a contradiction between the stabilization and training processes.

A similar contradiction between these processes occurs in automatic control systems. A. Feldbaum elaborated the theory of dual control under such contradictions [8]. For ASIs, various methods are being actively developed to control different plants in feedback systems rather efficiently [9–13]. All the works cited were devoted, to some extent, to overcoming this contradiction.

The closed-loop system in ASIs is stabilized using recurrent estimation methods [14–18] and active identification methods (with search procedures and test signals). However, the implementation of active strategies is associated with limitations of the normal operation mode [19] and difficulties in estimating search losses [20]. Therefore, the issue of choosing between active or passive identification, or a combination of these methods, has no universal solution and must be settled anew for almost every new plant.

In ASIs with the associative search algorithm in the closed loop, an identification problem also arises due to the singularity of the correlation matrix, which is used to build the model. This problem is partially eliminated by solving the system of equations through the Moore–Penrose procedure [21–23]. However, a knowledge base is required for the associative search algorithm to function. For some plants, such a knowledge base cannot be constructed. This may be due to significant changes in the plant during operation or its relatively short lifespan (insufficient to obtain the necessary amount of data).

Therefore, it is topical to develop identification and control algorithms that simultaneously solve the joint identification and control problem, at least for a limited class of plants.

In this paper, we present identification and control algorithms simultaneously solving the joint identification and control problem for a static linear plant. The application of these algorithms generates a new kind of ASIs with several distinctive features from the conventional ASIs as follows. First, the control signal is not transmitted to the identifier. Second, the control parameter is not directly estimated by the identifier (its value affects the estimates of the system parameters at the input disturbances). And third, the controller produces the control signal only based on the estimates of the system parameters at the input disturbances.

1. PROBLEM STATEMENT

Consider a static plant of the form

$$y_N = A_N^{\mathrm{T}} X_N + b_N u_N, \tag{1}$$

where $H_N^{\mathrm{T}} = \left[A_N^{\mathrm{T}} \vdots b_N \right]$ is the vector of plant's parameters; $A_N^{\mathrm{T}} = \left[a_{1,N}, a_{2,N}, ..., a_{n,N} \right]$ is the n-dimensional vector of unknown plant's parameters at (observable) input disturbances; b_N is the unknown parameter at the control signal (control parameter); N denotes the discrete time; $X_N = [x_{1,N}, ..., x_{n,N}]$ is the n-dimensional vector of observable input disturbances (the input vector); finally, u_N is the (scalar) control signal.

Equations (1) describe various industrial plants [1], particularly in metallurgy [3] and oil refining [24].

It is required to develop an identification algorithm for the unknown parameters A_N of the plant and a control algorithm that will stabilize a given value of the plant's output simultaneously with parameter identification.

2. ADAPTIVE AND CONTROL ALGORITHMS FOR A PREDICTIVE CONTROL SYSTEM OF THE LINEAR PLANT

For the sake of simplicity, let the desired output of system (1) be $y_{0,N} = 0$ (a stabilization system for the zero value).

We calculate the control signal u_N in the stabilization system by the formula

$$u_N = \frac{K_{N-1}^{\mathrm{T}} X_N}{-b^*}, \tag{2}$$

where $K_N^{\mathrm{T}} = \left[k_{1,N}, k_{2,N}, ..., k_{n,N}\right]$ is the vector of the estimates of the system parameters at the input disturbances; and b^* is the control parameter estimate. (The choice of this estimate will be discussed in detail below.)

For the stabilization system (1), (2), we use an adaptive algorithm of the form

$$K_N = K_{N-1} + \frac{y_N}{X_N^{\mathrm{T}} X_N} X_N. \tag{3}$$

The application of the adaptive algorithm (3) and the controller (2) generates a new kind of ASIs (Fig. 1), in contrast to the conventional ones (Fig. 2). The schemes for designing control systems similar to that in Fig. 2 were presented in [1, 25, 26].

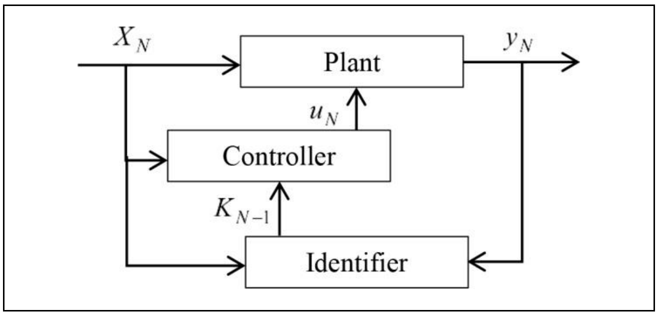

Fig. 1. The new kind of ASIs.

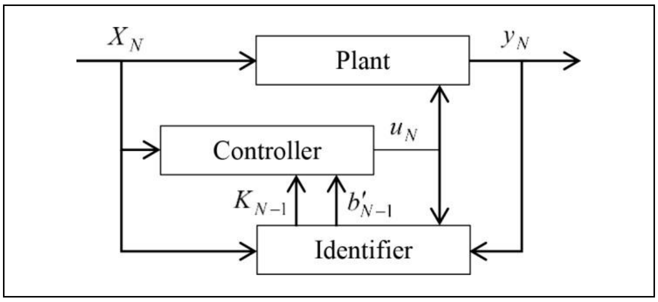

Fig. 2. Conventional ASIs.

The proposed system fundamentally differs from conventional ASIs: the control signal is not transmitted to the identifier; the control parameter is not directly estimated by the identifier (its value affects the estimates of the system parameters at the input disturbances); and the controller produces the control signal only based on the estimates of the system parameters at the input disturbances.

Algorithm (3) is a relaxation algorithm for estimating the parameters $\frac{1}{\beta} A_N$ of the n-dimensional linear plant with the input vector X_N and the relaxation factor $\beta = \frac{b_N}{b^*}$.

We demonstrate this fact. In view of equations (1) and (2), from equation (3) it follows that

$$K_N = K_{N-1} + \frac{A_N^{\mathrm{T}} X_N - \frac{b_N}{b^*} K_{N-1}^{\mathrm{T}} X_N}{X_N^{\mathrm{T}} X_N} X_N.$$

Letting

$$\beta = \frac{b_N}{b^*} \tag{4}$$

and extracting β from the fraction yield

$$K_N = K_{N-1} + \beta \frac{\frac{1}{\beta} A_N^{\mathrm{T}} X_N - K_{N-1}^{\mathrm{T}} X_N}{X_N^{\mathrm{T}} X_N} X_N. \tag{5}$$

The expression $\frac{1}{\beta} A_N^{\mathrm{T}} X_N$ in equation (5) is nothing but the output of the linear plant with the parameter vector $\frac{1}{\beta} A_N$ and the input disturbance vector X_N. Considering the form of equation (5), we finally arrive at the desired result.

Relaxation algorithms for estimating the parameters of linear plants were discussed in the monograph [3]. As shown therein, the estimates provided by relaxation algorithms under random input disturbances converge in mean square to the plant's parameters if the correlation matrix of the disturbances is nonsingular and the relaxation factor β satisfies the inequality

$$0 < \beta < 2. \tag{6}$$

Hence, for the convergence of algorithm (3), the control parameter estimate b^* shall be chosen so that the value of β (4) satisfies inequality (6). (This choice is based on available a priori data on the value of b_N, obtained during a preliminary study of the plant.)

The estimates K_N generated by algorithm (3) converge to the parameter vector $\frac{1}{\beta} A_N$, and this vector ensures the solution of the stabilization problem for system (1), (2). Indeed, formula (2) leads to

$$u_N = -\frac{\frac{b^*}{b_N} A_N^{\mathrm{T}} X_N}{b^*},$$

and consequently,

$$u_N = -\frac{A_N^{\mathrm{T}} X_N}{b_N}. \tag{7}$$

With the expression (7) substituted into formula (1), we cancel like terms to get the identity

$$y_N = 0,$$

i.e., the stabilization problem is completely solved.

The influence of the factor β on the convergence rate of relaxation algorithms was studied in the monograph [3].

The maximum convergence rate is achieved if $\beta = 1$.

For $1 < \beta < 2$, an upper relaxation occurs. In addition, increasing the value of β reduces the convergence rate, and the convergence process for individual components of the parameter vector becomes more and more nonmonotonic.

In the case $\beta < 1$, the convergence rate decreases for smaller values of β, but the convergence process for individual components becomes more and more monotonic.

The authors also analyzed the convergence rate of relaxation algorithms of various degrees depending on the correlation of the input disturbances, their means and variances, as well as the capabilities of relaxation algorithms to track time-varying plant's parameters and the influence of β on the tracking process [3].

Assume that the system output y_N is subject to an additive noise ε_N with zero mean and a variance σ_ε^2. Then the expression (3) takes the form

$$K_N = K_{N-1} + \frac{y_N + \varepsilon_N}{X_N^{\mathrm{T}} X_N} X_N. \tag{8}$$

By performing the same operations over (8) as when deriving (5), we obtain the expression

$$K_N = K_{N-1} + \beta \frac{\left(\frac{1}{\beta} A_N^{\mathrm{T}} X_N - K_{N-1}^{\mathrm{T}} X_N\right) + \frac{1}{\beta}\varepsilon_N}{X_N^{\mathrm{T}} X_N} X_N. \tag{9}$$

With

$$\Theta_N = \frac{1}{\beta} A_N - K_N, \tag{10}$$

equation (9) turns into

$$K_N = K_{N-1} + \beta \frac{\Theta_{N-1}^{\mathrm{T}} X_N + \frac{1}{\beta}\varepsilon_N}{X_N^{\mathrm{T}} X_N} X_N. \tag{11}$$

Due to the expression (11), the effect of the noise on algorithm (3) is analogous to that of the noise $\frac{1}{\beta}\varepsilon_N$ on the relaxation algorithm for estimating the parameters $\frac{1}{\beta} A_N$ of the linear plant with the input vector X_N.

Now, let the components of the vector X_N obey the Gaussian distribution, be mutually uncorrelated, and have zero mean and identical variances σ_X^2. Then, based on the results of [3], we have

$$\lim_{N\to\infty} M\Theta_N^2 = \frac{1}{\beta(2-\beta)} \cdot \frac{\sigma_\varepsilon^2}{(n-2)\sigma_X^2}, \; n > 2, \tag{12}$$

where *M* denotes the expectation operator.

As is easily verified, the output y_N of system (1) is given by

$$y_N = \beta \Theta_{N-1}^{\mathrm{T}} X_N. \tag{13}$$

Recall that the input disturbance vector X_N and the error vector are statistically independent. Hence, by squaring (13), taking its mean, and passing to the limit as $N \to \infty$, in view of (12), we obtain

$$\lim_{N\to\infty} My_N^2 = \frac{\beta}{(2-\beta)^2 (n-2)} \sigma_\varepsilon^2, \; n > 2. \tag{14}$$

Equality (14) characterizes the limit stabilization accuracy in system (1), (2) with the adaptive algorithm (3) under statistically independent, identically distributed input disturbances and the output measured with additive noise.

Direct analysis of equation (14) leads to the following conclusions.

When decreasing the value of β from 1 to 0, the convergence rate of algorithm (3) is reduced, but its noise immunity is simultaneously improved. Thus, when the training process ends, the stabilization error can be lowered by decreasing β until the reduction in the convergence rate violates the reliable tracking of the time-varying plant's parameters. We discuss the transition from one value of β to another below.

When increasing β from 1 to 2, the stabilization error grows to infinity (at $\beta = 2$); and the convergence rate of the algorithm is reduced.

Based on these considerations, in real control systems, the value of β should be chosen below 1.

To decrease β by a factor of l at the Nth step, the vector K_N and the value of b^* should be changed to

$$K_N^{'} = \frac{1}{l} K_N \quad (15)$$

and

$$b^{'*} = \frac{1}{l} b^*, \quad (16)$$

respectively.

With the coordinated change of K_N (15) and b^* (16), the control signal u_{N+1}, calculated according to K_N and b^* (on the one hand) and according to $K_N^{'}$ and $b^{'*}$ (on the other hand), will be identical. The value of y_{N+1} will also remain the same. Changes in the algorithm's operation will occur at the (N + 1)th step due to the refinement of the vector K_{N+1}: its magnitude varies, while the refinement value remains the same as it would have been without changing the value of β.

Now, assuming that $y_{0,N} \neq 0$, we introduce the following notation:

$y_N^{'} = y_N - y_{0,N}$ is the difference between the system output and the desired output value;

$X_N^{\mathrm{T}} = [X_N^{\mathrm{T}} \vdots y_{0,N}]$ is the augmented (n + 1)-dimensional input vector;

$K_N^{\mathrm{T}} = [K_N^{\mathrm{T}} \vdots k_{n+1,N}]$ is the augmented (n + 1)-dimensional vector of the estimates of the disturbance parameters;

$A_N^{'\mathrm{T}} = [A_N^{\mathrm{T}} \vdots -1]$ is the (n + 1)-dimensional augmented vector of the disturbance parameters.

We calculate the control signal u_N by the formula

$$u_N = \frac{K_{N-1}^{\mathrm{T}} X_N}{-b^*}. \quad (17)$$

The estimates $K_N^{'}$ are obtained using the algorithm

$$K_N^{'} = K_{N-1}^{'} + \frac{y_N - y_{0,N}}{X_N^{\mathrm{T}} X_N^{'}} X_N^{'}. \quad (18)$$

Clearly, (1) implies the equality

$$y_N^{'} = A_N^{'\mathrm{T}} X_N^{'} + b u_N. \quad (19)$$

In view of equality (19) and the above notation, the control system (1), (17) with the adaptive algorithm (18) is essentially a system for stabilizing $y_N^{'}$.

For the mean-square convergence of algorithm (18) under random input disturbances, just as before, their correlation matrix must be nonsingular. In this case, $y_{0,N}$ is required to be statistically independent of the input disturbances. This requirement holds, e.g., if $y_{0,N} = \mathrm{const}$.

In this case (no noises), $k_{n+1,N}$ converges to $-\frac{b_N}{b^*}$. Therefore, $b_N^{'} = -\frac{b^*}{k_{n+1,N}}$, converging to b_N as $N \to \infty$, can serve as the latter's estimate. Thus, for the stabilization system of a nonzero output value, it is possible to estimate the coefficient at the control signal and, consequently, the coefficients at the disturbances.

3. NUMERICAL SIMULATION

As an example, consider a plant with a 10-dimensional input vector X_N. Assume that its components belong to a random sequence of uniformly distributed numbers on the interval [–1, 1]. Let the plant's parameter vector be $A_N^{\mathrm{T}} = (1;\, 2;\, 3;\, 1.5;\, 1.6;\, 2.2;\, 2.5;\, 2.9;\, -1;\, -2)$, $b_N = 1$; and let the initial value of the vector K_N be $K_0^{\mathrm{T}} = (0.5;\, 0;\, 0;\, 0;\, 0;\, 0;\, 0;\, 0;\, 0;\, 0)$.

The plant's operation was simulated in MATLAB with $N = \overline{1,100}$ and averaging over 100 realizations. In all the figures below, except Figs. 3 and 15, the data are averaged over 100 realizations.

First, the operation of the plant without control was simulated. The plant with the open control loop was identified using the Kaczmarz algorithm.

The simulation results are presented in Figs. 3 and 4. The mean-square value of the output, i.e., the squared difference between the output and zero (the given output value, see the beginning of Section 2), for a single realization is 14.28. And the mean-square identification error of the plant's parameters (the squared difference between the estimates of the plant's parameters and their real values, averaged over 100 realizations) rapidly decreases to nearly zero.

For the closed-loop system, the stabilization algorithm (3) was applied. The operation of the plant was simulated under the control parameter estimates b^* = 1.33 ($\beta = 0.75$), b^* = 1 ($\beta = 1$), and b^* = 0.8 ($\beta = 1.25$).

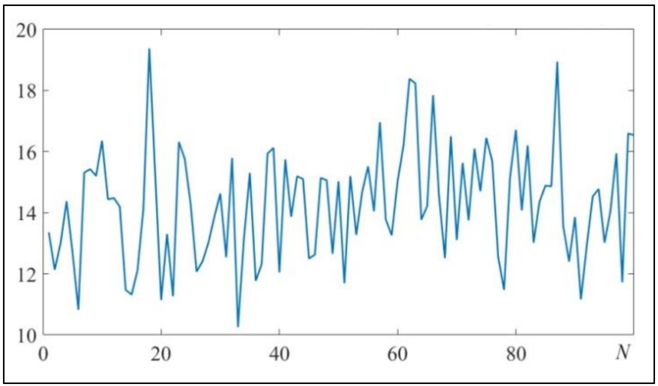

Fig. 3. The mean-square value of the plant's output in the open-loop system.

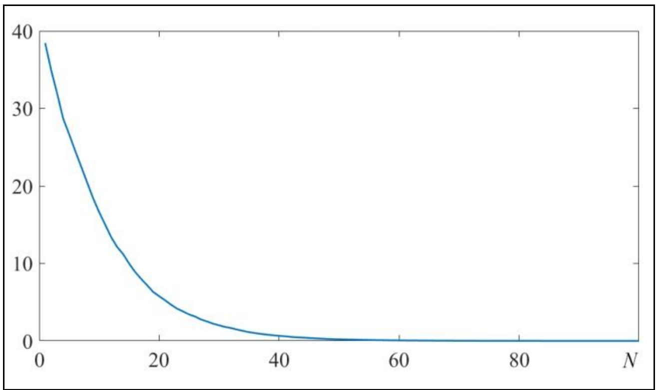

Fig. 4. The mean-square identification error of the plant's parameters in the open-loop system.

According to the simulation results (Figs. 5–7), the convergence rate of the identification process in the closed-loop system is almost equal to that in the open-loop one; and the mean-square stabilization error of the output (the squared difference between the output and its given zero value, averaged over 100 realizations) rapidly decreases to nearly zero. The estimates of the plant's parameters in Fig. 7 are scaled depending on the control parameter estimate b^*.

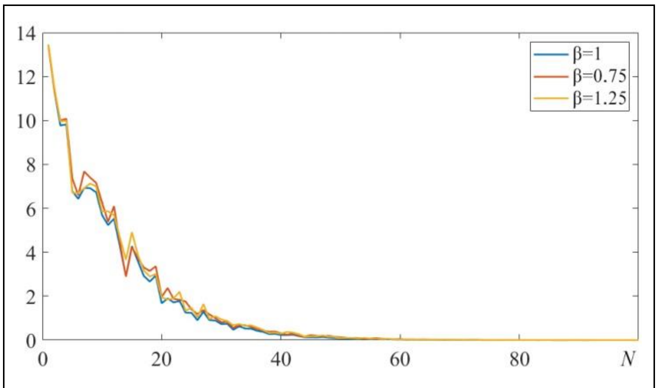

Fig. 5. The mean-square stabilization error of the plant's output in the closed-loop system.

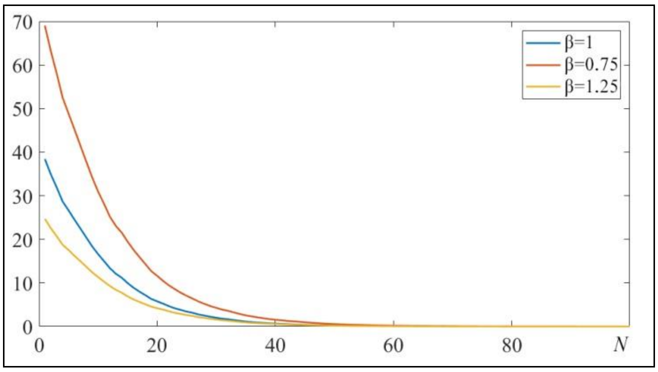

Fig. 6. The mean-square identification error of the plant's parameters in the closed-loop system.

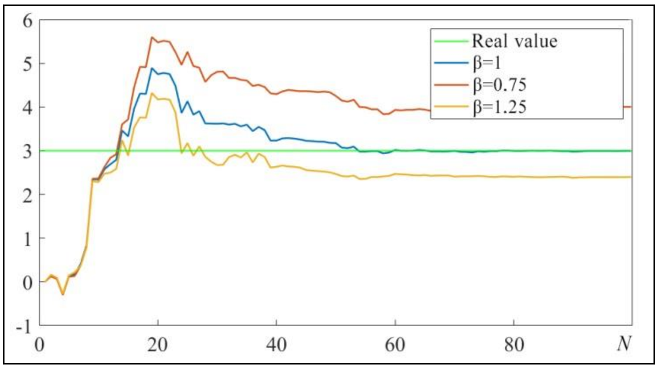

Fig. 7. The convergence of one parameter to the plant's parameter.

Figure 8 shows the correlation matrix obtained by the closed-loop system simulation. All 100 realizations were used to calculate the matrix. Obviously, the output and control in this system are almost statistically uncorrelated. The relationship between the output and the input disturbances is very weak. (This relationship arose during the system's training stage.) Thus, the output is practically statistically independent of the input disturbances and control (a consequence of appropriate output stabilization), and the disturbance control system for the plant demonstrates an ideal performance.

Note the nearly zero value of the matrix determinant (4·10^$^{-15}$): it can be considered singular. However, despite this fact, the system is trained effectively and controls the plant simultaneously.

The plant's operation was simulated in the case of increasing the value of a single parameter by a factor of 1.5 at the 50th step. (The third component of the plant's parameter vector was selected due to its maximum absolute value.) The objective was to assess the trained system's capability to track the parameter change and quickly stabilize the output again.

According to Figs. 9 and 10, the system effectively handles even a relatively large step change in the plant's parameter: it can work with time-varying plants.

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	u	y
x_1	1.0000	-0.0025	0.0016	-0.0030	0.0068	-0.0201	0.0081	-0.0149	0.0182	0.0051	-0.1380	0.0241
x_2	-0.0025	1.0000	0.0100	-0.0002	0.0258	-0.0093	-0.0063	-0.0074	-0.0060	0.0094	-0.2895	0.0954
x_3	0.0016	0.0100	1.0000	-0.0053	0.0164	-0.0110	0.0096	0.0111	0.0011	0.0026	-0.4429	0.1465
x_4	-0.0030	-0.0002	-0.0053	1.0000	-0.0018	0.0065	-0.0021	-0.0156	0.0172	0.0156	-0.2000	0.0727
x_5	0.0068	0.0258	0.0164	-0.0018	1.0000	-0.0025	0.0122	0.0182	0.0010	-0.0051	-0.2639	0.0741
x_6	-0.0201	-0.0093	-0.0110	0.0065	-0.0025	1.0000	-0.0084	-0.0023	-0.0002	0.0170	-0.2981	0.1059
x_7	0.0081	-0.0063	0.0096	-0.0021	0.0122	-0.0084	1.0000	-0.0002	-0.0133	0.0047	-0.3650	0.1230
x_8	-0.0149	-0.0074	0.0111	-0.0156	0.0182	-0.0023	-0.0002	1.0000	0.0151	0.0091	-0.4143	0.1414
x_9	0.0182	-0.0060	0.0011	0.0172	0.0010	-0.0002	-0.0133	0.0151	1.0000	0.0127	0.1423	-0.0445
x_{10}	0.0051	0.0094	0.0026	0.0156	-0.0051	0.0170	0.0047	0.0091	0.0127	1.0000	0.2739	-0.0966
u	-0.1380	-0.2895	-0.4429	-0.2000	-0.2639	-0.2981	-0.3650	-0.4143	0.1423	0.2739	1.0000	-0.0021
y	0.0241	0.0954	0.1465	0.0727	0.0741	0.1059	0.1230	0.1414	-0.0445	-0.0966	-0.0021	1.0000

Fig. 8. The correlation matrix.

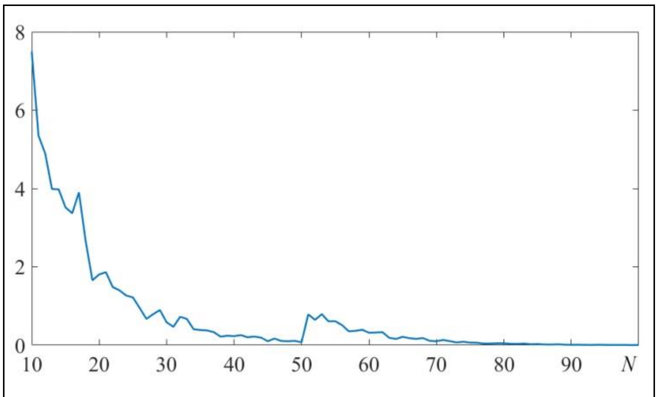

Fig. 9. The mean-square stabilization error of the plant's output when increasing a single parameter by a factor of 1.5.

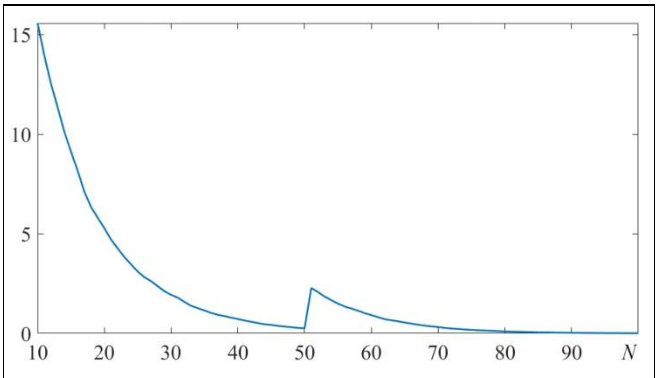

Fig. 10. The mean-square identification error of the plant's parameters when increasing a single parameter by a factor of 1.5.

Also, the plant's operation was simulated in the case of increasing the value of the control parameter by a factor of 1.2 at the 50th step.

Based on the simulation results (Figs. 11 and 12), the system effectively handles a relatively large step change in the plant's control parameter.

Finally, the plant's operation was simulated under measurement noise at the plant's output. An additive noise ε_N was supplied to the plant's output, consisting of a random sequence of uniformly distributed numbers in the closed interval [–2, 2]. The variance of the noise was set to 1.33. The variance of the open-loop plant's output was 15: an 8% noise component affected the plant's output.

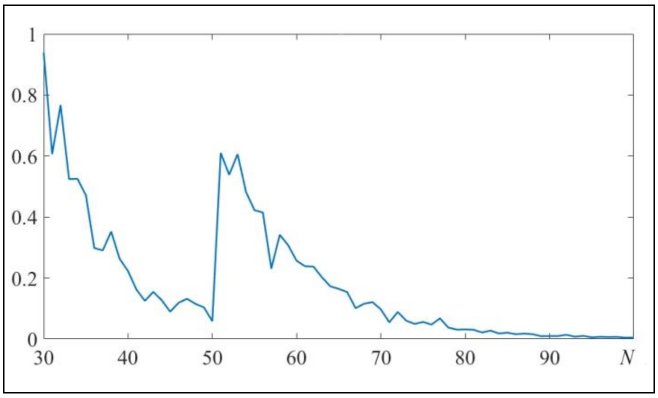

Fig. 11. The mean-square stabilization error of the plant's output when increasing the control parameter by a factor of 1.2.

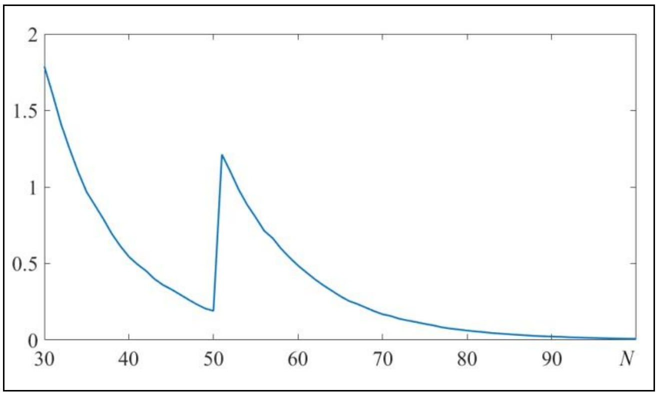

Fig. 12. The mean-square identification error of the plant's parameters when increasing the control parameter by a factor of 1.2.

Figures 13 and 14 demonstrate the effective operation of the plant in noise conditions. The best performance of the stabilization system is achieved at the lowest value of β (in the case under consideration, β = 0.5); see the discussion in Section 2. In addition, the output's variance after system training is approximately half the noise variance: the system has good performance under the noise affecting the plant's output.

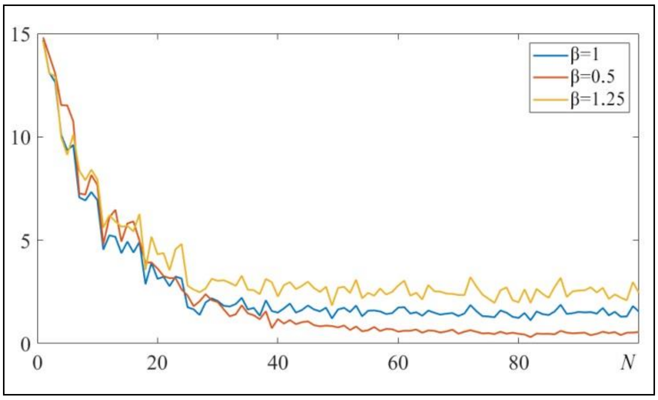

Fig. 13. The mean-square stabilization error of the plant's output under noise.

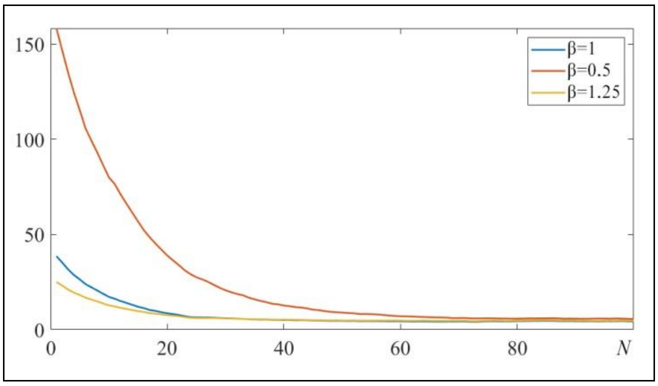

Fig. 14. The mean-square identification error of the plant's parameters under noise.

According to Figs. 13 and 14, by varying β, one can tune the algorithm's properties, choosing between convergence rate and noise immunity. The change of β during operation at an arbitrary step has been described in Section 2.

For a single realization with β = 0.5, Fig. 15 also illustrates the high effectiveness of the algorithm.

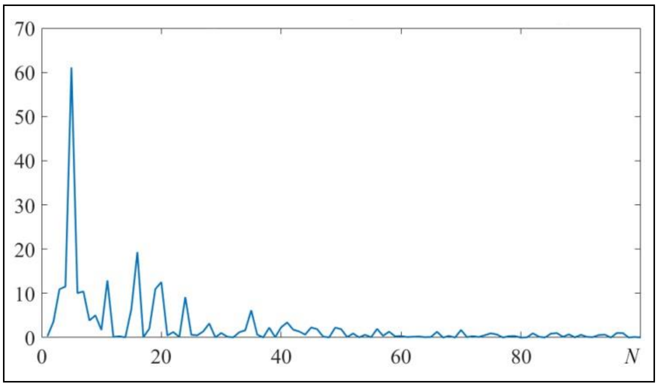

Fig. 15. The squared value of the plant's output under noise and β = 0.5 in a realization.

CONCLUSIONS

According to the analysis of the methods and algorithms for building modern ASIs, the statistical dependence of control on input disturbances leads to challenges in the operation of the systems. Moreover, this dependence is stronger for better-trained systems; therefore, it is necessary to find a trade-off between system training and control. Various algorithms and methods of control and plant identification are used here.

The identification and control algorithms proposed above solve both identification and disturbance control problems for a linear static plant. (Within this approach, control of dynamic plants will be considered in future work.) In the case of random input disturbances, the parameter estimates yielded by these algorithms have been shown to converge in mean square to the plant's parameters under the following conditions: the correlation matrix of the input disturbances is nonsingular; the ratio of the control parameter estimate to its real value is less than 2 by magnitude, and this estimate has the same sign as the control parameter. Furthermore, these algorithms can be applied to track time-varying plant's parameters. The limit stabilization accuracy in the system has been estimated under statistically independent, identically distributed input disturbances and the output measured with additive noise.

Numerical simulations have been conducted. According to the simulation results, the system based on these algorithms is trained quickly and maintains a given output value effectively; even step changes in the plant's parameters, including the control parameter, are properly handled. We emphasize the good performance of the system under an additive noise at the plant's output.

The application of the adaptive algorithm and controller proposed generates a disturbance control system of a new kind. This system has several distinctive features: the control signal is not transmitted to the identifier; the control parameter is not directly estimated by the identifier (its value affects the estimates of the system parameters at the input disturbances); and the controller produces the control signal only based on the estimates of the system parameters at the input disturbances.

The application of these algorithms in ASIs for industrial plants will significantly increase their performance by reducing system training losses: in this case, no special control is required for training. According to the authors' experience of work with industrial plants, such algorithms can be used in the petrochemical industry and the production of mineral fertilizers.

REFERENCES

1. Rajbman, N.S. and Chadeev, V.M., *Identification of Industrial Processes: The Application of Computers in Research and Production Control*, translated by Gerretsen, F.W., and edited by Eykhoff, P., Amsterdam: North-Holland Publishing, 1980.
2. Bakhtadze, N. and Yadikin, I., Discrete Predictive Models for Stability Analysis of Power Supply Systems, *Mathematics*, 2020, vol. 8, no.11, art. no. 1943.
3. Danilov, F.A., Imedadze, V.V., Klempert, E.D., et al., *Adaptivnoe upravlenie tochnost'yu prokatki trub* (Adaptive Control of Pipe Rolling Accuracy), Danilov, F.A. and Rajbman, N.S., Eds., Moscow: Metallurgiya, 1980. (In Russian.)
4. Bakhtadze, N.N., Lototsky, V.A., Maximov, E.M., and Maximova, N.E., Intelligent Algorithms of Power Grids State Identification, *Journal of Information Technologies and Computing Systems*, 2011, no. 3, pp. 45–50. (In Russian.)
5. Bakhtadze, N. and Lototsky, V., Knowledge-Based Models of Nonlinear Systems Based on Inductive Learning, in *New Frontiers in Information and Production Systems Modelling and Analysis. Incentive Mechanisms, Competence Management, Knowledge-based Production*, Różewski, P., Novikov, D., Bakhtadze, N., and Zaikin, O., Eds., Cham: Springer, 2016, vol. 98, pp. 85–104.
6. Bakhtadze, N., Chereshko, A., Elpashev, D., et al., Associative Model Predictive Control, *IFAC PapersOnLine*, 2023, vol. 56, no. 2, pp. 7330–7334.
7. Lototsky, V.A., Chadeev, V.M., Maximov, E.M., Bakhtadze, N.N., Tumanov, N.A., Mironov, V.E., and Tumanov, D.N., Nonlinear Dynamic Predictor. The Experimental Testing Results for "Ammophos-2" Line at "Voskresensk Mineral Fertilizers", Inc., *Proceedings of the 3rd International Conference "System Identification and Control Problems" (SICPRO'04)*, Moscow: Trapeznikov Institute of Control Sciences, January 28–30, 2004, p. 49. (In Russian.)
8. Feldbaum, A.A., Dual Control Theory. I, *Avtomatika i Telemekhanika*, 1960, vol. 21, no. 9, pp. 1240–1249. (In Russian.)
9. Görges, D., Relations between Model Predictive Control and Reinforcement Learning, *IFAC Papers OnLine*, 2017, vol. 50, no. 1, pp. 4920–4928.
10. Balakrishnan, S.N., Ding, J., and Lewis, F.L., Issues on Stability of ADP Feedback Controllers for Dynamical Systems, *IEEE Transactions on Systems, Man, and Cybernetics Part B (Cybernetics)*, 2008, vol. 38, no. 4, pp. 913– 917.
11. Liu, F., Sun, J., Si, J., et al., A Boundedness Result for the Direct Heuristic Dynamic Programming, *Neural Networks*, 2012, vol. 32, pp. 229–235.
12. Sokolov, Y. and Kozma, R., Improved Stability Criteria of ADP Control for Efficient Context-Aware Decision Support Systems, *Proceedings of the 2013 International Joint Conference on Awareness Science and Technology and Ubi-Media Computing*, Aizuwakamatsu, Japan, 2013, pp. 41–47.
13. Jiang, Y. and Jiang, Z.P., Robust Adaptive Dynamic Programming and Feedback Stabilization of Nonlinear Systems, *IEEE Transactions on Neural Networks and Learning Systems*, 2014, vol. 25, no. 5, pp. 882–893.
14. Chen, H.F., Recursive System Identification and Adaptive Control by Use of the Modified Least Squares Algorithm, *SIAM J. Control and Optimization*, 1984, vol. 22, no. 5, pp. 758–776.
15. Gevers, M., Identification for Control: From the Early Achievements to the Revival of Experiment Design, *European Journal of Control*, 2005, vol. 11, no. 4–5, pp. 335–352.
16. Goodwin, G.C. and Sin, K.S., *Adaptive Filtering: Prediction and Control*, 1st ed., Hoboken: Prentice Hall, 1984.
17. Sastry, S. and Boston, M., *Adaptive Control: Stability, Convergence, and Robustness*, Hoboken: Prentice Hall, 1994.
18. Stefanovic, M., Wang, R., and Safonov, M.G., Stability and Convergence in Adaptive Systems, *Proceedings of American Control Conference*, Boston, MA, 2004. DOI: 10.23919/ACC.2004.1386862
19. Shteinberg, Sh.E. and Zalutskii, I.E., Adaptation of Standard Controllers to Operating Conditions in Industrial Regulation Systems, *Industrial Automatic Control Systems and Controllers*, 2003, no. 4, pp. 11–14. (In Russian.)
20. Rotach, V.Ya., Adaptation in Process Control Systems, *Industrial Automatic Control Systems and Controllers*, 2005, no. 1, pp. 4–10. (In Russian.)
21. Penrose, R., A Generalized Inverse for Matrices, *Proceedings of the Cambridge Philosophical Society*, 1955, vol. 51, pp. 406–413.
22. Moore, E., On the Reciprocal of the General Algebraic Matrix, *Bulletin of the American Mathematical Society*, 1920, vol. 26, pp. 394–395.
23. Albert, A., *Regression and the Moore–Penrose Pseudoinverse*, New York–London: Academic Press, 1972.
24. Klimchenko, V.V., Samotylova, S.A., and Torgashov, A.Y., Feedback in a Predictive Model of a Reactive Distillation Process, *Journal of Computer and Systems Sciences International*, 2019, vol. 58, no. 4, pp. 637–647.
25. Luo, X., A Constrained Recursive Adaptive Predictive Control Method with Lagrange Polynomials, *Modelling and Simulation in Engineering*, 2025, vol. 2025, art. no. 5824720.
26. Bamimore, A., Akomolafe, D.A., Asubiaro, P.J., and Osunleke, A.S., A Comparison of Two Methods of Adaptive Nonlinear Model Predictive Control, *IFAC PapersOnLine*, 2024, vol. 58, no. 25, pp. 90–95.

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