Improving The Safety Stability Of Algorithms For Recurrent State Estimation Based On The Methods Of Conditionally Gaussian Filtering.

Kadirov D.T[1] - Rasulev.A.X [2], Gaibnazarov S.B[3]., Nosirova S.SH.[4], Urmanov .I.R [5]-

The teacher of Namangan Institute of Engineering and Technology [1]
The teacher of Tashkent State Technical University [2 3 4 5]
Email address: akb-81@mail.ru

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Abstract: In the world, research is underway to create a universal approach to assessing the state of stochastic control objects, focused on solving problems of adaptive control of dynamic objects. In this regard, an important task is to improve and modify methods and algorithms for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering in conditions of various kinds of disturbances and noises. [1]

Currently, the Republic pays great attention to the areas of automation and control, including the creation of advanced control systems that provide energy and resource savings in the automation and management of various technological processes and industries. The Strategy for the Further Development of the Republic of Uzbekistan for 2017–2021 sets out the tasks "... to reduce the energy intensity and resource intensity of the economy, to widely introduce energy-saving technologies into production, and to increase labor productivity in the sectors of the economy." In this aspect, the creation of effective algorithms for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering, which contribute to improving the accuracy and quality indicators of control processes, is very important.

Key words: Adaptive estimation, methods of conditionally Gaussian filtering, states of dynamical systems, recurrence relations, low-temperature separation.

This article provides the results of the study to a certain extent serves to fulfill the tasks provided for by the Decree of the President of the Republic of Uzbekistan No. UP-4947 of February 7, 2017 "On the Strategy of Actions for the Further Development of the Republic of Uzbekistan" and Resolutions No. PP-3151 of July 27, 2017 "On Measures to further expand the participation of industries and sectors of the economy in improving the quality of training of specialists with higher education "and No. PP-3682 of April 27, 2018" On measures to further improve the system of practical implementation of innovative ideas, technologies and projects ", as well as in other regulatory legal documents adopted in this area.

However, the constant complication and expansion of the range of scientific research requires the development of new effective methods and algorithms for adaptive identification, state estimation and control under conditions of uncertainty based on the concepts of conditionally Gaussian filtering. Regularized algorithms for conditionally optimal filtering of control objects with a nonparametric description of correlated noises, adaptive estimation of the state of control objects taking into account parametric disturbances also require development. In addition, it turns out to be expedient to develop stable algorithms for suboptimal estimation of the state of control objects, an extended state vector of controlled objects, as well as algorithms for stable multistep estimation of the state of nonlinear control objects. In connection with the above, there is an urgent need for further modification and creation of effective algorithms for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering. [2-3]

Research objectives:

system analysis of the development of methods and algorithms for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering;

development of stable algorithms for conditionally optimal filtering of control objects with a nonparametric description of correlated noises;

development of regular algorithms for adaptive estimation of the state of control objects taking into account parametric disturbances;

development of stable algorithms for suboptimal adaptive estimation of the state of control objects;

development of algorithms for stable multistep estimation of the state of nonlinear control objects;

practical testing of the developed algorithms and computational schemes for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering when solving the problem of synthesizing an adaptive control system for a specific technological object.

The object of the research is the algorithms for estimating the state of stochastic control objects based on the methods of conditionally Gaussian filtering.

The subject of the research is methods and algorithms for adaptive regular estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering.

Research methods. The dissertation work uses the methods of system analysis, identification, assessment, adaptive control and solving incorrectly posed problems.

The scientific novelty of the research is as follows:

stable algorithms for conditionally optimal filtering of control objects have been developed for nonparametric description of correlated noises based on the block version of the Gauss - Seidel method;

Regular algorithms for adaptive estimation of the state of control objects have been developed taking into account parametric disturbances on the basis of a stable procedure for inverting ill-conditioned undefined matrices;

stable algorithms for suboptimal adaptive estimation of the state of control objects have been developed on the basis of recurrent algorithms for finding pseudoinverse matrices;

algorithms have been developed for stable multistep estimation of the state of nonlinear control objects based on the method of reduction of suboptimal filtering procedures using the concepts of stable pseudo-inversion of non-negative definite matrices.

The practical results of the study are as follows:

based on the results of an industrial experiment under normal functioning conditions, mathematical models of the process of low-temperature gas separation in the production of natural gas have been developed;

structural and functional schemes of automation and adaptive control of the technological process of low-temperature gas separation have been developed;

a system for controlling the technological process of low-temperature gas separation with the appropriate technical support is proposed, which makes it possible to stabilize the technological modes of the processes and increase its efficiency.

The reliability of the research results. The reliability of the research results obtained is ensured by the implementation of methodically substantiated theoretical calculations; the application of theoretically grounded concepts of adaptive assessment of the state; the use of proven methods and algorithms of the modern theory of automatic control; the required degree of convergence of the proposed methods and algorithms for adaptive control; the results of theoretical and applied research and their mutual consistency.

Scientific and practical significance of the research results. The scientific significance of the research results lies in the development of constructive algorithms for adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering.

The practical significance of the results of the work lies in the development of mathematical and algorithmic support for the problems of adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering. The developed algorithms can be widely used in the construction of a functional structure and automation of the design of adaptive control systems for technological processes with a continuous nature of production.

Implementation of research results. Based on the results of the adaptive estimation of the state of stochastic control objects based on the methods of conditionally Gaussian filtering, the following are introduced**:**

the developed regular algorithms for adaptive estimation of the state of control objects, taking into account parametric disturbances, have been introduced at Muborakneftgaz LLC (Help of Kazneftgazkazibchikarish JSC No. 05 / 09-58zh dated January 30, 2019). As a result, the accuracy of calculating the parameters of the regulators is increased;

stable algorithms for suboptimal adaptive assessment of the state of control objects have been developed and implemented at Muborakneftgaz LLC (Reference of Kazneftgazkazibchikarish JSC No. 05 / 09-58zh dated January 30, 2019). The algorithms allow stabilizing the technological modes of the low-temperature gas separation process.

the developed algorithms for sustainable multistep assessment of the state of nonlinear control objects have been introduced at Muborakneftgaz LLC (Reference of Kazneftgazkazibchikarish JSC No. 05 / 09-58zh dated January 30, 2019). As a result, the accuracy of determining the parameters of the object and disturbances is increased.

When implementing algorithms for stable adaptive estimation of the state of control objects based on the methods of conditionally Gaussian filtering, a nonparametric covariance method is often used, which avoids possible computational difficulties caused by the poor conditioning of high-dimensional matrices, since in this case the extended covariance equations are replaced by subsystems of low-order equations. Let us present a regular algorithm for solving the problem under consideration. [4-5]

Consider the problem of estimating the state of a linear system of the form

$$x_{k+1} = A_k x_k + \Gamma_k w_k \,, \qquad (1)$$

$$y_{k+1} = C_{k+1} x_{k+1} + v_{k+1} \,, \qquad (2)$$

– vectors of state, measurement, noise in the object, and noise in the dimension meter x_k, y_{k+1}, w_k, v_{k+1} respectively n, l, p, l - matrix functions of the discrete argument of the (A_k, C_{k+1})corresponding dimensions, the pair ( ) is a Kalman observable for all, and $E\{w_k w_{k-i}^T\} = Q_k(i)$, $E\{v_{k+1}v_{k+1-i}^T\} = R_{k+1}(i)$, $(k, i = \overline{0,N})$, $E\{x_0 w_i^T\} = V_0(i)$, $E\{x_0 v_{i+1}^T\} = W_0(i+1)$.

Let's consider approximations of noise in the object and in the measurements by order autoregression models :

$$w_{k+1} = \sum_{j=0}^{\alpha} \Phi_{k-j} w_{k-j} + \xi_k, \qquad v_{k+1} = \sum_{j=0}^{\beta} \Lambda_{k-j} v_{k-j} + \eta_k, \tag{3}$$

where is ξ_k white noise with a covariance matrix that is not correlated with $w_0, w_{-1}, \ldots, w_{-\alpha}$; η_k - white noise that is not correlated with and has a covariance matrix .
The main vulnerable procedure in the considered filtering problem for nonparametric assignment of correlated noise is the estimation of matrices and in Φ_{k-j} и Λ_{k-j} в (3). We present a regular algorithm for estimating matrices , Λ_{k-j} which can also be used for evaluating matrices.

The matrices of the model (3) Φ_{k-j} $(j = \overline{0,\alpha})$, Q_{ξ_k} (3) can be estimated on the basis of matrix equations of the form:

$$Q_{k+1}^T(1,\gamma) = Q_k(\gamma,\alpha)\Phi_k^T(1,\alpha), \quad Q_{k+1}(0) = \Phi_{k+1}(1,\alpha)Q_k(\alpha,\alpha)\Phi_k^T(1,\alpha) + Q_{\xi_k}, \tag{4}$$

where $\alpha \le \gamma < s$, and block matrices $\Phi_k(1,\alpha)$, $Q_k(1,\gamma)$, $Q_k(\gamma,\alpha)$ have the following structure

$$\Phi_k(1,\alpha) = [\Phi_k, \Phi_{k-1}, \ldots, \Phi_{k-\alpha}], \quad Q_{k+1}(1,\gamma) = [Q_{k+1}(1), Q_{k+1}(2), \ldots, Q_{k+1}(\gamma+1)],$$

$$Q(\gamma,\alpha) = \left[\begin{array}{c:c:c:c} Q_k(0) & Q_k^T(1) & \cdots & Q_k^T(\alpha) \\ \hdashline Q_k(1) & Q_{k-1}(0) & \cdots & Q_{k-1}(\alpha-1) \\ \hdashline \vdots & \vdots & & \vdots \\ \hdashline Q_k(\alpha) & Q_{k-1}(\alpha-1) & \cdots & Q_{k-\alpha}(0) \\ \hdashline Q_k(\alpha+1) & Q_{k-1}(\alpha) & \cdots & Q_{k-\alpha}(1) \\ \hdashline \vdots & \vdots & & \vdots \\ \hdashline Q_k(\gamma) & Q_{k-1}(\gamma-1) & \cdots & Q_{k-\alpha}(\gamma-\alpha) \end{array}\right]$$

Equation (4) is written as:

$$Q_{k+1,j}^T(1,\gamma) = Q_k(\gamma,\alpha)\Phi_{k,j}^T(1,\alpha), \tag{5}$$

$Q_{k+1,j}^T(1,\gamma)$ and $\Phi_{k,j}^T(1,\alpha)$ –j- $Q_{k+1}^T(1,\gamma)$, $\Phi_k^T(1,\alpha)$ columns of the matrices, respectively, $j = 1,2,\ldots,p$.

Given the large dimension of the matrix, $Q_k(\gamma,\alpha)$ when solving equation (5), we will use a block version of the Gauss-Seidel method for normal systems of equations using " microiterations»:

$$d_r = Q_{k,l}^{+}(\gamma,\alpha)\phi_r, \quad \Phi_{k,j,r+1}^T(1,\alpha) = \Phi_{k,j,r}^T(1,\alpha) + \xi I_l d_r,$$

$l = l(r) = (r \bmod p) + 1$; $\{l(r)\}_{l=0}^{\infty}$ – a periodic $\phi_{r+1} = \phi_r - \xi Q_{k,l}(\gamma,\alpha)d_r$, sequence of the form $1,2,\ldots,\alpha+1,\ 1,2,\ldots,\alpha+1,\ldots$; $I = (I_1 I_2 \ldots I_{\alpha+1})$; $I_l \in R^{p \times p_j}$; $I -$ is a unit matrix of order n.

If is an arbitrary vector, and satisfies the matching condition, $\Phi_{k,j,0}^T(1,\alpha)$ then, where is the pseudo $\phi_0 = Q_{k+1,j}^T(1,\gamma) - Q_k(\gamma,\alpha)\Phi_{k,j,0}^T(1,\alpha)$, $\Phi_{k,j,r}^T(1,\alpha) \xrightarrow{r\to\infty} \Phi_{k,j,*}^T(1,\alpha)$, $\Phi_{k,j,*}^T(1,\alpha)$ – -solution of the system of equations (5).

The given stable iterative algorithms for conditionally optimal filtering of linear control systems with a nonparametric description of correlated noise reduce the computational complexity and increase the speed and accuracy of the iterative process of calculating noise approximation matrices. [6-8]

When solving various problems of synthesis of control systems for dynamic objects, the problem of estimating the state vector of the controlled object based on the Kalman filter, taking into account parametric perturbations, arises. We write down the equations for the error of the perturbed filter and the random component $\delta P_i^{(v)}$:

$$\delta\hat{x}_{i+1} = L_0\delta\hat{x}_i + L_1\delta A_{i+1}^{(v)} + L_2\delta H_{i+1}^{(v)} + L_3\delta Q_{i+1}^{(v)} + L_4\delta R_{i+1}^{(v)} + L_5\delta P_i^{(v)}. \quad (6)$$

$$\delta P_{i+1}^{(v)} = N_0\delta P_i^{(v)} + N_1\delta A_{i+1}^{(v)} + N_2\delta H_{i+1}^{(v)} + N_3\delta Q_{i+1}^{(v)} + N_4\delta R_{i+1}^{(v)}\ , \quad (7)$$

The functional nature of this equation allows us to obtain the equations of the desired filter based on the methods of the theory of conditional Gaussian filtration. The algorithm for estimating a stochastic object in the presence of parametric perturbations can be written as:

$$\hat{Z}_{i+1} = G_c + G_L\hat{Z}_i + \left(G_L J_i A_c^T\right)F^+\left(\hat{x}_{i+1} - A_c\hat{Z}_i\right), \quad (8)$$

$$J_{i+1} = G_L J_i G_L^T + G_N D_\xi G_N^T - G_L J_i A_c^T F^+ A_c J_i G_L^T\ , \quad (9)$$

$$\hat{Z}_0 = M(Z_0) = \begin{bmatrix} \hat{x}_0 \\ 0 \\ 0 \end{bmatrix},\quad J_0 = \left[\begin{array}{c:c:c} D_{\delta x} & D_{\delta x} & 0 \\ \hdashline D_{\delta x} & D_{\delta x} & \\ \hdashline 0 & & D_{\delta P} \end{array}\right],$$

$$F = E_p + A_c J_i A_c^T\ , \quad (10)$$

When:

$$D_\xi = \left[\begin{array}{c:c:c:c} D_{A_{i+1}} & & & 0 \\ \hdashline & D_{H_{i+1}} & & \\ \hdashline & & D_{Q_{i+1}} & \\ \hdashline 0 & & & D_{R_{i+1}} \end{array}\right]\cdot\delta_{(i+1,j+1)};\quad A_c = [1\quad 1\quad 0]\otimes A_{i+1/i}\,;$$

$$E_p = \left[K_{i+1}H_{i+1}A_{i+1/i} \;\vdots\; K_{i+1}H_{i+1} \;\vdots\; K_{i+1}\right]\left[\begin{array}{c:c:c} P_{i/i-1} & & 0 \\ \hdashline & Q_{i+1} & \\ \hdashline 0 & & R_{i+1} \end{array}\right]\left[K_{i+1}H_{i+1}A_{i+1/i} \;\vdots\; K_{i+1}H_{i+1} \;\vdots\; K_{i+1}\right]^T$$

,

where is the $D_{\delta x}$ covariance matrix of errors in determining the vector of the initial estimate; $D_{\delta P}$ - the covariance matrix of errors in determining the matrix of a priori covariances ; P_0; $D_{A_{i+1}}\delta_{(i+1,j+1)}$, $D_{H_{i+1}}\delta_{(i+1,j+1)}$, $D_{Q_{i+1}}\delta_{(i+1,j+1)}$ и $D_{R_{i+1}}\delta_{(i+1,j+1)}$ and-the corresponding intensity matrices; $\otimes$ - the Kronecker product symbol.

A matrix of the form (10), the pseudo-F^+ inverse of which is used in (8) and (9) to evaluate and, is a symmetric ill-conditioned sign-defined matrix. In order to stabilize the desired solution Z and J give greater numerical stability to the pseudo-circulation procedure in (8), (9), it is necessary to use regular methods. In the implementation of (8) and (9), the regularized Cholesky method of factorization of symmetric matrices is used. [9-10]

These algorithms allow us to stabilize the matrix inversion procedure when estimating the state of stochastic objects and thereby increase the accuracy of determining the true estimate of the state vector when the object and observer parameters are perturbed.

The result of solving filtration problems is known to be optimal $Z^T(k+1) = [X^T(k+1), Y^T(k+1)]$:

$$Z(k+1) = \Phi_z[k+1,k;Z(k)] + \Gamma_z[k+1,k;Z(k)]N_z(k),\ k = 0,1,2,..., \quad (11)$$

where is $Z(k+1)$ a column vector of size; – $((n+m)\times 1$; $X(k+1)$ – $(n\times 1))$ is a dimensional unobservable component of the vector ; $Z(k+1)$; $Y(k+1)$ – a part of the vector components available for

direct observation; and $\Phi_z[\cdot]$ и $\Gamma_z[\cdot]$ –known vector functions of their arguments; $N_z(k)$ - vectors of independent Gaussian random variables.
Suppose that the functions included in the right-hand side of equation (11) have the form:

$$\Phi_z[k+1,k,Z(k)] = \Phi_{zx}[k+1,k;Y(k)]X(k) + \Phi_{zy}[k+1,k;Y(k)] =$$
$$= \begin{bmatrix} \Phi_{xx}[k+1,k;Y(k)]X(k) + \Phi_{xy}[k+1,k;Y(k)] \\ \Phi_{yx}[k+1,k;Y(k)]X(k) + \Phi_{yy}[k+1,k;Y(k)] \end{bmatrix},$$
$$\Gamma_z = \Gamma_z[k+1,k;Y(k)] = [\Gamma_x^T[k+1,k;Y(k)]\Gamma_y^T[k+1,k;Y(k)]]^T .$$

When implementing suboptimal discrete filtering algorithms, it is usually sought to reduce the overall computational cost. From this point of view, it is advisable to use a suboptimal algorithm for evaluating the form:

$$X^*(k+1) = \Phi_{xx}[k+1,k;Y(k)]X^*(k) + \Phi_{xy}[k+1,k;Y(k)] +$$
$$+ \overline{K}(k+1)\{Y(k+1) - \Phi_{yx}[k+1,k;Y(k)]X^*(k) - \Phi_{yy}[k+1,k;Y(k)]\}, \quad (12)$$

in which $\overline{K}(k+1)$ the suboptimal values of the transmission coefficient matrix and the covariance matrix $P(k+1)$ can be calculated using the formulas:

$$\overline{K}(k+1) = [\Phi_{xx}P(k)\Phi_{yx}^T + \Gamma_x\Gamma_y^T][\Phi_{yx}P(k)\Phi_{yx}^T + \Gamma_y\Gamma_y^T]^{-1}, \quad (13)$$

$$P(k+1) = \Phi_{xx}P(k)\Phi_{xx}^T + \Gamma_x\Gamma_x^T + [\Phi_{xx}P(k)\Phi_{yx}^T + \Gamma_x\Gamma_y^T]\times$$
$$\times[\Phi_{yx}P(k)\Phi_{yx}^T + \Gamma_y\Gamma_y^T]^{-1}[\Phi_{xx}P(k)\Phi_{yx}^T + \Gamma_x\Gamma_y^T]^T . \quad (14)$$

Thus, when calculating the matrices and in expressions (13) and (14), it is necessary to reverse the matrix $A(k) = [\Phi_{yx}P(k)\Phi_{yx}^T + \Gamma_y\Gamma_y^T]$. at each step . The efficiency of the suboptimal estimation algorithm (12) significantly depends on the accuracy of the inversion of this matrix.

Taking into account that the matrix in expressions (13) and (14) is square and positive definite, it is advisable to use the following recurrent relations:

$$\gamma_{t+1} = \gamma_t - \gamma_t a_{t+1}^T(a_{t+1}\gamma_t a_{t+1}^T)^+ a_{t+1}\gamma_t , \quad \gamma_0 = I ,$$
$$X_{t+1} = X_t + \gamma_t a_{t+1}^T(a_{t+1}\gamma_t a_{t+1}^T)^+(c_{t+1} - a_{t+1}X_t), \;\; X_0 = 0 ,$$

The accuracy of the calculations here is controlled by the traces of the matrices, γ_t, $t = 1,2,...,n$ depending on the conditionality of the matrix .

These algorithms allow us to improve the accuracy and stability of the procedure for suboptimal estimation of unobservable coordinates of random processes.

In many cases, when describing control objects, it is necessary to use nonlinear equations or nonlinear recurrent relations.
Let the equations of dynamics and measurements of a stochastic system be described by the difference equations $X_{k+1} = f(X_k,k) + \sigma(X_k,k)V_{1,k}$, $X \in R^n$, $V_1 \in R^T$, $k = 0,1,\,...,$

$Y_k = \varphi(X_k,k) + \psi(X_k,k)V_{2,k}$, $Y \in R^n$, $V_2 \in R^m$.

Here $-\{V_{1,k}\}$, $\{V_{2,k}\}$ are sequences of independent vectors, such that, for each, k $V_{1,k}$, $V_{2,k}$ are independent, normally distributed random variables. [11-12]

It is necessary to determine the best estimate of the process $\hat{X}_k$ from X_k observations in the root-mean-square sense $Y_1, Y_2, ..., Y_k$. . In the case of a high dimension of the vector X, it is advisable to use multi-step filtering algorithms that significantly reduce the number of equations that determine the estimate . To implement this approach, $X \in R^n$ the vector is divided into s subvectors, i.e. $X = [X_1^T, X_2^T, \dots, X_s^T]^T$, где $X_1 \in R^{n_1}$, $X_2 \in R^{n_2}$, $..., X_s \in R^{n_s}$ и $n_1 + n_2 + ... + n_s = n$.
In accordance with the accepted sequence of operations of this algorithm, for example, at the i-th step, the estimate is determined based on the following

recurrentrelations:

$$\hat{X}_{i,k+1} = \hat{X}_{i,k+1/k} + \alpha_{i,k+1}\beta^{-1}_{i,k+1}[Y_{k+1} - \bar{\varphi}_i + \bar{\varphi}_{x_i}\hat{X}_{i,k} - \bar{\varphi}_{x_i} X_{i,k+1/k}],$$

$$\hat{X}_{i,k+1/k} = \bar{f}_i(\hat{X}_{1,k}, ..., \hat{X}_{s,k}, k), \quad \alpha_{1,k+1} = [\bar{f}_{i\,x_i} P_{i,k} \bar{f}^T_{i\,x_i} + \sigma_i\sigma_i^T]\varphi^T_{x_i}, \qquad (15)$$

$$\beta_{i,k+1} = \bar{\varphi}_{x_i}[\bar{f}_{i\,x_i} P_{i,k} \bar{f}_{i\,x_i} + \sigma_i\sigma_i^T]\bar{\varphi}^T_{x_i} + \psi_i\psi_i^T, \; P_{i,k+1} = \bar{f}_{ix_i} P_{i,k} \bar{f}_{ix_i} - \alpha_{i,k+1}\beta^{-1}_{i,k+1}\alpha^T_{i,k+1} + \sigma_i\sigma_i^T.$$

The most time-consuming operation in the multistep estimation algorithm under consideration is the matrix inversion operation in $\beta_{i,k+1}$ (15). The accuracy and computational stability of the estimation algorithm significantly depends on the quality of the implementation of this procedure.

For stable pseudo-transformation $\beta_{i,k+1}$ of the matrix, the following relations were used:

$$\beta^{+}_{i,k+1} = T^T(TT^T)^{-2}T, \qquad (16)$$

$$\beta_{i,k+1} = T^T T.$$

If the matrix is $\beta_{i,k+1}$ poorly conditioned or degenerate, then to increase the stability of the pseudo – circulation procedure in (16), it is advisable to use regular procedures of the form:

$$\beta^{+}_{i,k+1} = T^*(TT^* + \alpha I)^{-2}T,$$

where $\alpha > 0$ is the regularization parameter, I is the unit matrix.

Here α it is advisable to determine the regularization parameter based on the method of model examples.

The above algorithms help to stabilize the computational procedure of matrix inversion, and thus to improve the accuracy of multistep estimation of the state of nonlinear stochastic systems.

It also considers the issues of constructing algorithms for stable adaptive estimation of the extended state vector of controlled objects. In their practical implementation, the computational schemes of the "moderate spoilage" method turn out to be effective.

"Application of the developed algorithms in the tasks of automation and control of the technological process of low-temperature gas separation" presents the results of the application of the developed algorithms for the synthesis of adaptive control systems based on the methods of conditionally Gaussian filtration in the automation and control of the technological process of low-temperature gas separation

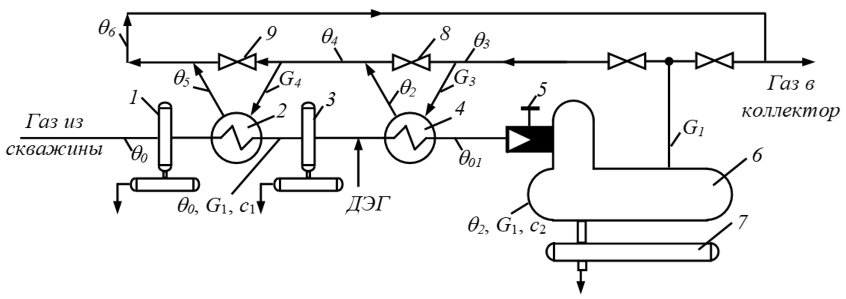


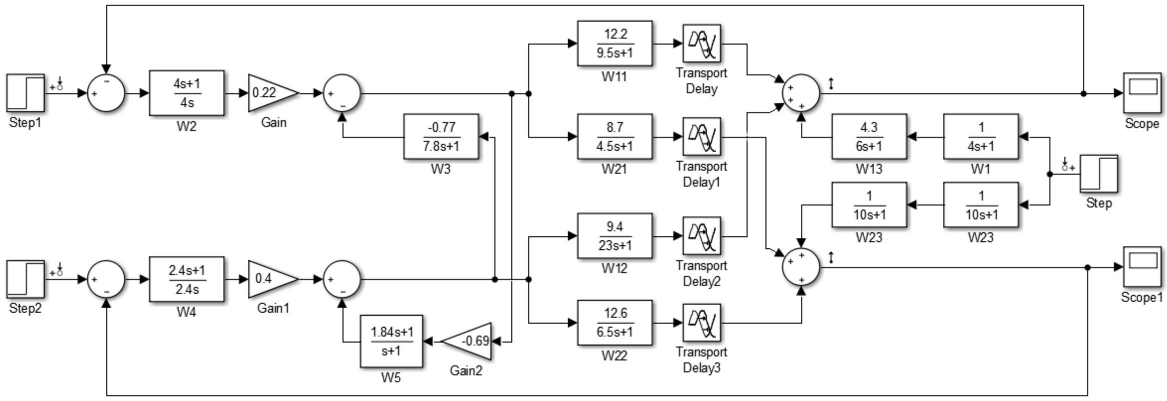
Fig. 1. Simplified design diagram of the low-temperature separation unit: 2 and 4 - the first and second stages of the heat exchanger; 5 - turbo expander; 1, 3 and 6 - separators; 7- separating tank, 8, 9 - gate valves; G1, G2, G3, G4 - gas flow rates at the corresponding points; (1, (2, (3, (4, (5, (6, are the gas temperatures at the corresponding points); c1 and c2) are the specific heat capacities of the hot and cold gas, respectively.

Analysis of literature data and the results of preliminary studies show that the process of low-temperature gas separation refers to multiply connected non-stationary control objects. In this regard, the problem of synthesis and analysis of an autonomous control system of the process under consideration under conditions of uncertainty is very urgent.

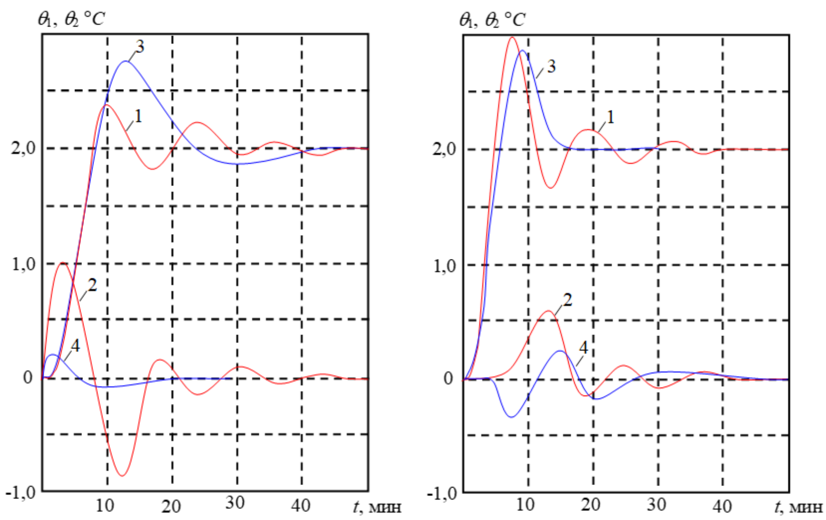
Experimental studies were carried out on six main channels: the position of the regulating body 8 - the temperature in the separator and at the point of introduction of diethylene glycol (DEG) - W11 and W21; the position of the regulating body 9 - temperature at the point of DEG injection and in the separator - W22 and W12; the position of the adjustable choke 5 - the temperature in the separator and at the DEG water point - W13 and W23.

The block diagram of the gas temperature control system is shown in Fig. 2. Proportional-integral controllers with transfer functions are used as control devices. Transfer functions of compensation devices and are

determined from the condition of independence of the controlled temperature from the change in the difference and the controlled temperature from the change in the difference, where and are the set temperature values.
Curves 1 and 2 of temperature changes at (Fig. 3) characterize the dynamics of temperature at the point of injection of the inhibitor and in the low-temperature separator in the system without compensation devices, and curves 3 and 4 - the dynamics of the same coordinates in the system with compensation devices.

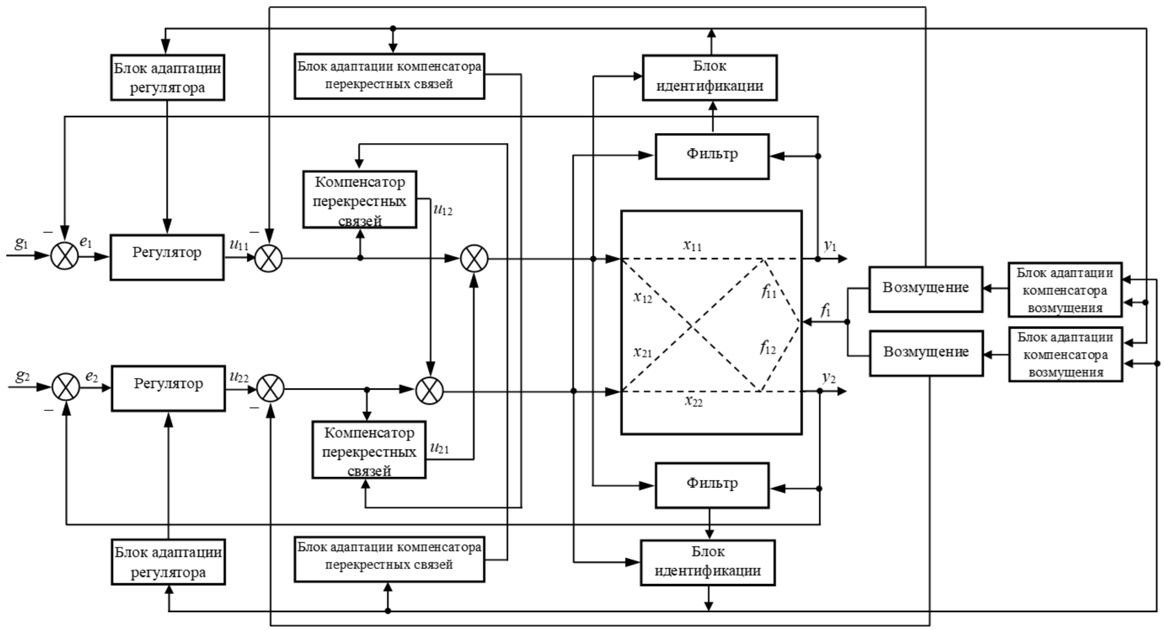


Pic . 2. Block diagram of the associated automatic gas temperature control system.



Pic . 3. Block diagram of the associated automatic gas temperature control system.
θ_{y1}=2ºC (a) и θ_{y2}=2ºC (б).

As can be seen from pic. 3, the control process is stable both with a coupled system and with two single-loop systems.
In real conditions of the functioning of the low-temperature separation process, the object is influenced by an external disturbance - the gas flow rate at the inlet of the low-temperature separation unit. The use of coupled control schemes in the presence of external disturbances and changes in the characteristics of the process does not provide the optimal operating mode of the technological object. In this case, the synthesis and use of connected-combined adaptive control systems, which significantly reduce and sometimes completely eliminate the effect on the output value of not only cross channels, but also external disturbances, due to the use of appropriate dynamic compensators, allows to obtain the best quality of object control. The development of the most efficient systems of this class is associated with the implementation of the principles of invariance, autonomy and adaptability. [thirteen]
In pic 4 shows a block diagram of the proposed adaptive autonomous invariant control system



Pic . 4. Block diagram of an adaptive autonomous invariant control system for the low-temperature separation process.

For identification, we write the equation of the object in the form: $x(t+1)=b_0+\sum_{i=1}^{n_1} b_i x(t+1-i)+\sum_{i=n_1+1}^{n} b_i x(t+1-\tau_1-i)+\sum_{j=1}^{m} b_{n+j} u(t+1-\tau-j)+\xi(t),$

(17)

where τ_1, τ - -discrete net delays, the control action has a limited amplitude; $u_1 \le u(t) \le u_2$; $b_i(i=0,...,n+m)-$ unknown parameters of the object $|\xi(t)| \le \xi_1$.

Equation (17) can be written as follows:

Уравнение (17) можно записать в следующем виде:

$$Y(t)=Z(t-1)\beta(t), \tag{18}$$

$$Y(t)=\left(y^T(t)\ \dots y^T(t-p+1)\right)^T,\ Z(t-1)=\left(z^T(t-1)\dots z^T(t-p)\right)^T,$$
$$y(k)=z(k-1)\beta(t),\quad k=t,t-1,...,t-p+1,$$
$$z(k)=(1,x(k),...,x(k+1-n_1),x(k-\tau_1-n_1),...x(k+1-\tau_1-n),u(k-\tau),...,u(k+1-\tau-m)),$$
$$\beta^T(t)=(b_0,b_1,...,b_{n+m}).$$

The vector of parameter increments is found from the criteria

$$\|e_0(t)-Z(t-1)\Delta\beta(t)\|^2=\min,\quad \|\Delta\beta(t)\|^2=\min,$$

$$\Delta\beta(t)=Z^+(t-1)(X(t)-Z(t-1)\beta(t-1)), \tag{19}$$

$$X(t)=\left(x^T(t)\dots x^T(t-p+1)\right)^T,\quad e_0(t)=X(t)-Z(t-1)\beta(t-1).$$

In order to ensure the stability of the pseudo-transformation procedure, we write the expression (19) in the form:

$$\Delta\beta(t)=(Z^T(t-1)Z(t-1)+\alpha I)^{-1}Z^T(t-1)(X(t)-Z(t-1)\beta(t-1)),$$

where α the regularization parameter should be determined based on the methods of quasi-optimality or relations.

After determining the increment, we find $\Delta\beta(t)$ the parameters themselves

$$\beta(t) = \beta(t-1) + \Delta\beta(t)\,. \tag{20}$$

The control for each moment of time is found from the quadratic criterion

$$(y(t+1+\tau) - x^{*}(t+1+\tau))^{2} = \min, \;\; u_1 \le u(t) \le u_2\,,$$

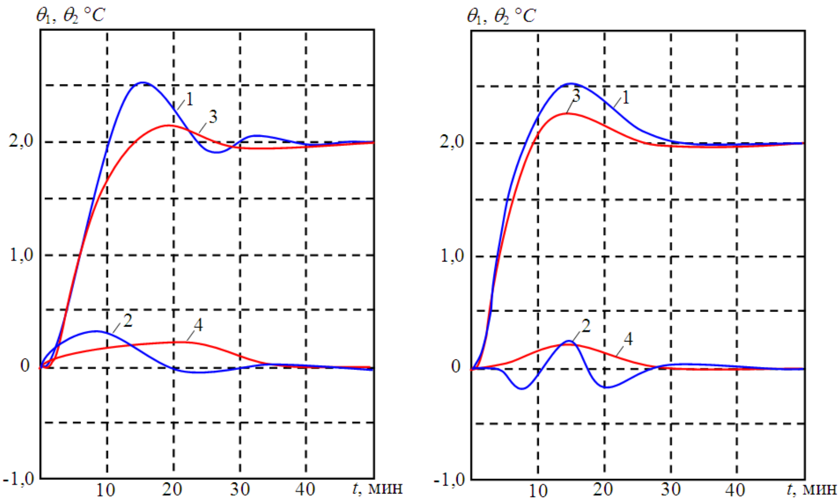
which leads to an equation of the form

$$u(t) = \begin{cases} u_1, & если \;\; v(t) < u_1, \\ v(t), & если \;\; u_1 \le v(t) \le u_2, \\ u_2, & если \;\; u_2 < v(t), \end{cases} \tag{21}$$

$$v(t) = \beta_{n+1}^{-1}(t)\left[x^{*}(t+1+\tau) - L(\beta'(t), y(t+\tau), u(t-1))\right],\;\; t \ge 0,$$

where $x^{*}(t+1)$ – the assigned trajectory at each point in time $t > 0$.

Based on the above expressions (18-20), the object was identified and the control action was formed in accordance with (21). The transition curves are shown in pic . 5



Pic . 5. Transients in adaptive Autonomous invariant control system with control θy1=2 o C (a) and θy2=2 o C (b) 1 and 2 – θ1(t) and θ2(t) the adaptation of the regulators; 3 and 4 - θ1(t) and θ2(t) the adaptation of Autonomous controllers and compensators

Output. Thus, the use of the proposed adaptive autonomous invariant control system based on algorithms for the current identification of the object and adaptation of control algorithms will improve the quality of control of the technological process of low-temperature gas separation under non-stationary conditions.

REFERENCES:

1. Егупов Н.Д., Пупков К.А. Методы Классической И Современной Теории Автоматического Управления. Учебник В 5 Томах. - М.: Издательство МГТУ Им.Н.Э.Баумана, 2004.
2. Алексеев В.М., Тихомиров В.М., Фомин С.В. Оптимальное Управление. -М.: Физматлит, 2005. – 384 С.
3. Технологические Основы И Моделирование Процессов Промысловой Подготовки Нефти И Газа: Учебное Пособие /Кравцов А.В. [И Др.]. Томск: Изд-Во Томского Политехн. Ун-Та, 2012. – 128 С.
4. Математическое Моделирование Химико-Технологических Процессов: Учебное Пособие / Ас.М.Гумеров, Н.Н.Валеев, Аз.М.Гумеров, В.М.Емельянов; Казан. Гос. Технол. Ун-Т. – Казань, 2006. – 216 С.
5. Кравцов А.В., Ушева Н.В., Мойзес О.Е., Кузьменко Е.А., Ануфриева О.В. Анализ Влияния Технологических Параметров И Оптимизация Процессов Низкотемпературной Сепарации // Известия Томского Политехнического Университета. 2009. Т. 315. №3. –С.57-60.
6. Ланчаков Г.А., Кульков А.Н., Зиберт Г.К. Технологические Процессы Подготовки Природного Газа И Методы Расчета Оборудования. -М.: Недра-Бизнесцентр, 2000. – 279 С.
7. Лежнина Ю.А. Робастное Управление Многосвязными Объектами С Запаздывающим Аргументом

// Приборы И Системы. Управление, Контроль, Диагностика. – 2011. – № 5. – С. 12–16.

8. Кудряшов В.С., Рязанцев С.В., Козенко И.А. Метод Моделирования И Реализации Многосвязных Автономно-Инвариантных Цифровых Систем Управления // Вестник ТГТУ. 2012. Том 18. № 2. – С. 350-360.
9. Бекмуратов Т.Ф., Захидов Б.А., Касымов С.С. Математические Модели И Алгоритмы Управления В Производстве Минеральных Удобрений. – Т.: Фан, 1984. –129 С.
10. Кудряшов В.С. Алгоритм Расчета Выходов Автономных Компенсаторов Многосвязной Цифровой Системы Управления / В.С.Кудряшов, С.В.Рязанцев, И.А.Козенко // Вестн. Воронеж. Гос. Технол. Акад. Сер. Информ. Технологии, Моделирование И Управление. – 2010. – № 2. – С. 21–26.
11. Паршева Е.А., Лежнина Ю.А. Робастное Децентрализованное Управление С Компенсацией Возмущений Нелинейными Многосвязными Объектами // Мехатроника, Автоматизация, Управление. – 2011. –№ 6. – С. 2–7.
12. Автоматическое Управление В Химической Промышленности: Учеб. Для Вузов. Под Ред. Е.Г.Дудникова. – М.: Химия, 1987. -368 С.
13. Рубан А.И. Синтез Алгоритмов Адаптивного Управления С Идентификацией // Аит, №10, 1983. – С.128-138.