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Algorithms for Adaptive Estimation of the State of Integrated Natural Gas Treatment Installations

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ABSTRACT: At present, more and more attention is paid, to the issue of energy efficiency in chemical production. However, modern methods for calculating the purification of natural gases are carried, out according to norms and standards that provide the possibility of calculating only on general terms. Questions of formation of algorithms of adaptive estimation of a condition of installations of complex preparation of gas are considered. Algorithms of adaptive estimation of the full and reduced vector of a condition on the basis of dynamic Kalman filters in the conditions of aprioristic uncertainty of covariation matrixes of noise of object and a hindrance of measurements are given. Actually adaptation in case of estimation of a full vector of a condition is made on the basis of iterative algorithm, in case of estimation of the reduced vector of a condition for calculation of a covariation matrix of an error of a filtration the updating sequence is used.

KEYWORDS: the gas condensate, automated technological complexes, installation of complex preparation of gas, control system, Kalman`s filter, noise and hindrances, iterative methods, kovariatsionny matrixes, an assessment.

1. INTRODUCTION

Increasing quality requirements for field treatment of gas and condensate for transport and further processing, commissioning and design of high-performance equipment, development of new environmentally friendly technologies for production and preparation of well products require the creation of reliable and efficient means and systems for automatic control and management of gas production processes.

Modern control systems for gas field technological processes must carry out most of the operations performed by maintenance personnel and ensure the maximum possible output of gas and condensate with the required quality indicators, subject to reliable and trouble-free operation of the equipment. Currently, the development and implementation of automated technological complexes (ATC) for gas condensate washing based on interconnected technological facilities and installations and their corresponding automated control systems for technological processes of production, collection and field treatment of gas and condensate is underway.

ATC gas condensate field are designed to intensify technological processes, increase the reliability of their operation and in the future transition to unmanned well production preparation technology. The introduction of ATK involves the widespread use of micromodular and microprocessor technology for local automatic control systems, the use of control microcomputers both in control loops and at the top level of the hierarchy, including the tasks of collecting and processing technological information [1-3].

The main technologically important facilities of the gas condensate field are integrated gas treatment units (GTP). In the structure of a modern gas production enterprise, the GTP is a direct technological link that performs planned gas and condensate treatment under conditions of their uneven consumption and limited ability to measure a number of parameters of the processed gas-liquid products. Increasing the volumes and improving the quality of gas and condensate during the field preparation of wells at the gas processing unit with technological lines of low-temperature separation is an urgent task of national economic importance.

The use of optimal control systems for GTP facilities will ensure a reduction in losses of commercial products, improve its quality, reduce the cost of material and labor resources for gas and condensate field treatment by minimizing the time to reach the optimal modes of technological parameters and their stabilization during operation under existing random disturbances, as well as automation of the calculation of the optimal parameters of local control systems of the GTP [3-5].

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For the practical implementation of the optimal control systems of the GTP, it is necessary to estimate the variable states of the control system and their derivatives at the current time. Not all state variables are measurable, and besides, the measurements are noisy.

It is advisable to estimate the coordinates of the state vector of local control systems of the GTP, which are inaccessible to direct measurement, and the coordinates of the disturbance vector using the Kalman digital filter algorithm in a form convenient for implementation on a control microcomputer.

Consider a system described by the equations:

$$x_{i+1} = A_i x_i + B_i u_i + \Gamma_i w_i , \tag{1}$$

$$z_i = H_i x_i + v_i , \tag{2}$$

where x_i - is the state vector of the system of dimension n; u_i - is the control vector of dimension l; z_i - is the observation vector of dimension m; w_i and v_i are vectors of object noise and observation noise of dimensions q and p, respectively, which are a sequence of the form of Gaussian white noise with characteristics $E[w_i]=0$, $E[w_i w_k^T] = Q\delta_{ik}$, $E[v_i]=0$, $E[v_i v_k^T] = R\delta_{ik}$, $E[w_i v_k^T] = 0$; A_i, B_i, Γ_i and H_i are matrices of the corresponding dimensions, δ_{ik} - is the Kronecker symbol.

Since system (1) is linear, and the initial state, noise and interference are Gaussian, its state at any time is also Gaussian. In addition, if we take into account the Gaussian nature of noise and interference, and assume the linearity of equation (2), then we can make the assumption that the measurements will also be Gaussian for all i [5-9]. These statistics are defined by the Kalman filter equations:

$$\hat{x}_{i|i-1} = A_{i,i-1}\hat{x}_{i-1|i-1} + B_{i,i-1}u_{i-1} , \tag{3}$$

$$\hat{x}_{i|i} = \hat{x}_{i|i-1} + K_i \left[z_i - B_{i,i-1}u_{i-1} - H_i \hat{x}_{i|i-1} \right] , \tag{4}$$

where:

$$K_i = P_{i|i-1} H_i^T \left[H_i P_{i|i-1} H_i^T + R_i \right]^{-1} , \tag{5}$$

$$P_{i|i-1} = A_{i|i-1} P_{i-1|i-1} A_{i|i-1}^T + Q_{i-1} , \tag{6}$$

$$P_{i|i} = P_{i|i-1} - K_i H_i P_{i|i-1} , \tag{7}$$

and the initial conditions are:

$$\hat{x}_{0|-1} = \mu_0 ,\ P_{0|-1} = M_0 .$$

Equations (3)-(7) describe the mean, covariance and hence the Gaussian posterior density function for the system corresponding to equations (1)-(2).

This approach makes it possible to synthesize control systems based on the separation principle [6]. In accordance with this principle, the procedure for estimating the parameters or state variables is performed separately from the calculation of the parameters of the control device.

In connection with the above mentioned in the theory and practice of building control systems for dynamic objects of various functional purposes, the issues of estimating the state vector of controlled objects in the presence of object noise and measurement noise are of great importance. In real conditions of functioning of controlled objects, external noise-signal conditions can vary over a wide range.

An important property of the optimal filter is that the residual terms, defined as $v_i = z_i - H_i \hat{x}_{i|i-1}$, are a white noise type sequence. In this case, the covariance of the remainder term is equal to $C_0 \overset{\Delta}{=} E\left[v_i v_i^T\right] = HPH^T + R$, and the autocovariance matrix of process y_i is equal to:

$$C_j \overset{\Delta}{=} E\left[v_{i+j} v_i^T\right] = H\left[A(I - KH)\right]^{j-1} A\left[PH^T - KC_0\right], \tag{8}$$

at $j = 1,2,3,...,$ where K - is an arbitrary gain.

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Under conditions where the noise covariance matrices Q and R are unknown, the gain matrix K in the Kalman filter cannot be determined. If, however, the gain can be chosen such that:

$$C_0^T K^T = HP^T, \tag{9}$$

the gain is found to be optimal. And vice versa, if the gain is optimal, then equation (9) is valid.

To solve equation (9), we will use iterative methods [10-11]. There is a whole family of iterative methods that can be used to solve equation (9) when operator C_0^T has a continuous inverse. The simplest is the method of simple iteration: $k_{i+1}^j = k_i^j - \beta_i J' k_i^j$, $\quad i = 0,1,2,...,$ where $\beta > 0$ is some constant, which is chosen from the condition of convergence of the sequence of approximations $\{k_i^j\}$ to the exact solution; k^j – *j*-th column of matrix K^T; $j = 1,2,...p$; $J(k) = \frac{1}{2}\left\| C_0^T K^T - HP^T \right\|^2$.

Quite often, the state vector of managed objects may contain components that are observable according to the measurements used [6-9]. This implies the expediency of dividing the full state vector x_i^{Π} into the observed vector x_i and the unobserved vector ζ_i. Using the reduced filter, which, based on the mathematical model for the full state vector x_i^{Π}, estimates only some components of the state vector, on the one hand, allows decoupling from the unobservable components of the full vector state x_i^{Π}, on the other hand, it simplifies the computational estimation procedure.

Consider the system:

$$x_{i+1}^{\Pi} = A_{i+1|i} x_i + \Gamma_{i+1|i} w_i, \tag{10}$$

$$z_{i+1} = H_{i+1} x_{i+1}^{\Pi} + v_{i+1}, \tag{11}$$

We divide vector x_{i+1}^{Π} into an estimated state vector and an unestimated displacement vector ζ_i. Then, by dividing matrices $A_{i+1|i}$, $\Gamma_{i+1|i}$ into the corresponding blocks, we can obtain the equations of the system in the following form:

$$\begin{bmatrix} x_{i+1} \\ \hdashline \zeta_{i+1} \end{bmatrix} = \begin{bmatrix} A_{i+1|i} & \Lambda_{i+1|i} \\ 0 & \psi_{i+1|i} \end{bmatrix} \begin{bmatrix} x_i \\ \hdashline \zeta_i \end{bmatrix} + \begin{bmatrix} 0 \\ \hdashline \Gamma_{i+1|i} \end{bmatrix} w_i,$$

$$z_{i+1} = \begin{bmatrix} H_{i+1} & 0 \end{bmatrix} \begin{bmatrix} x_{i+1} \\ \hdashline \zeta_{i+1} \end{bmatrix} + v_i.$$

The filter equation can also be written in block form:

$$\begin{bmatrix} \hat{x}_{i+1} \\ \hdashline \hat{\zeta}_{i+1} \end{bmatrix} = \begin{bmatrix} A_{i+1|i} & \Lambda_{i+1|i} \\ 0 & \psi_{i+1|i} \end{bmatrix} \begin{bmatrix} \hat{x}_i \\ \hdashline \hat{\zeta}_i \end{bmatrix} + \begin{bmatrix} K_{i+1}^1 \\ \hdashline K_{i+1}^2 \end{bmatrix} \left(z_{i+1} - \begin{bmatrix} H_{i+1} & 0 \end{bmatrix} \begin{bmatrix} A_{i+1|i} & \Lambda_{i+1|i} \\ 0 & \psi_{i+1|i} \end{bmatrix} \begin{bmatrix} \hat{x}_i \\ \hdashline \hat{\zeta}_i \end{bmatrix} \right).$$

Assuming that $\hat{\zeta}_{i+1} = 0$, we can write:

$$\hat{x}_{i+1} = A_{i+1|i}\hat{x}_i + K_{i+1}^1 \left(z_{i+1} - H_{i+1} A_{i+1|i} \hat{x}_i \right), \tag{12}$$

where K_{i+1}^1 is found from expressions K_{i+1}, $P_{i+1|i}$, P_i made for the full state vector $\hat{x}_i^{\Pi}$.

Thus, equation (12) describes a reduced filter that evaluates only vector x_{i+1}, i.e., part of the full state vector x_{i+1}^{Π}. The estimate $\hat{x}_{i+1}$ given by the reduced filter will no longer be optimal, since estimate $\hat{\zeta}_{i+1}$ is not taken into account in the structure of equation (12). It should be noted that the full optimal filter, when estimating the vector $\hat{x}_{i+1}$, also takes into account the estimate $\widehat{\zeta}_{i+1}$. Therefore, the reduced filter simplifies the computational procedure, but the estimate $\widehat{x}_{i+1}$ becomes suboptimal [6, 7].

In this case, the adaptive reduced filter equation can be represented as:

$$\widehat{x}_i = A_{i,i-1}\widehat{x}_{i-1} + K_i\left(z_i - H_i A_{i,i-1}\widehat{x}_{i-1}\right),$$
$$K_i = P_{i|i-1}H_i^T\left[H_i P_{i|i-1}H_i^T + R_i\right]^{-1},$$
$$P_i = P_{i|i-1} - K_i H_i P_{i|i-1},$$
$$P_{i+1|i} = K_i\left(v_i v_i^T\right)K_i^T + P_i,$$

where $v_i = z_i - H_i A_{i,i-1}\widehat{x}_{i-1}$.

The above relations can be used in the synthesis of local control systems for the main stages of complex gas treatment at a gas production enterprise.

REFERENCES

[1] Repin N.N., Tagiev V.G. Optimal control of natural gas complex treatment plants. M.: Nedra, 1992. - 187 p.
[2] Nikonenko I.S. Creation of automated control systems in gas production. - M.: Nedra, 2001. -192 p.
[3] Korotaev Yu.P., Tagiev V.G., Gergedava Sh.K. System modeling of optimal modes of operation of natural gas production facilities. - M.: Nedra, 1989. -264 p.
[4] Shukurova O.P. Modelirovaniye i optimizatsiya protsessa osushki gaza v mnogofunksionalnix absorberov. // Mejdunarodniy nauchno-texnicheskiy jurnal «Ximicheskaya texnologiya. Kontrol i upravleniye». –Tashkent, 2012. – №4(46). –S.86-88.
[5] Handbook on the theory of automatic control // Ed. A.A. Krasovsky. - M.: Nauka, 1987. - 712 p.
[6] Filtering and stochastic control in dynamical systems // Ed. K. T. Leondes Per. from English, - M.: Mir, 1980. - 407 p.
[7] Pervachev S.V., Perov A.I. Adaptive message filtering. - M.: Radio and communication, 1991. - 160s.
[8] Igamberdiev H.Z., Yusupbekov A.N., Karimov D.R., Shukurova O.P. Stable Algorithms for Adaptation of Objects with Control Delay. ICSCCW 2019: 10th International Conference on Theory and Application of Soft Computing, Computing with Words and Perceptions - ICSCCW-2019. 735-740 p.
DOI https://doi.org/10.1007/978-3-030-35249-3_95
[9] Ogarkov M.A. Methods of statistical estimation of parameters of random processes. –M.: Energoatomizdat, 1990. -208 p.
[10] Bakushinsky A.B., Goncharsky A.V. Iterative methods for solving ill-posed problems. -M.: Nauka, 1989. -128 p.
[11] Alifanov O.M., Artyukhin E.A., Rumyantsev S.V. Extreme methods for solving ill-posed problems. - M.: Nauka, 1988. - 288 p.