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Utkir Uktam oʻgʻli Kholmanov
Tashkent State Technical University Address: 2 Universitetskaya st., 100095, Tashkent city, Republic of Uzbekistan E-mail: xolmanov0902@mail.ru, Phone:+998-94-408-09-02;, xolmanov0902@mail.ru

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Utkir Uktam o'g'li Kholmanov

Tashkent State Technical University
Address: 2 Universitetskaya st., 100095, Tashkent city, Republic of Uzbekistan
E-mail: xolmanov0902@mail.ru, Phone:+998-94-408-09-02;

Abstract: *A modified Kalman filter of the glass cooking process is synthesized, taking into account perturbations in the form of a sequence of colored noises. The possibility of expanding this filter by noise filters to improve functioning in the presence of low-frequency disturbances is studied and a corresponding estimation scheme with additional noise filters is proposed. The results of the simulation allow us to assume that low-frequency disturbances in the glass furnace act at the input and affect the state of the control object.*
Keywords: *observer, Kalman filter, simulation, mathematical model, glass furnace.*

Аннотация: *Рангли шовқинлар кетма-кетлиги кўринишидаги ғалаёнларни ҳисобга олган ҳолда шишани пишириш жараёни учун модификацияланган Калман фильтри синтезланган. Ушбу фильтрни, шовқинлар фильтри ҳисобига паст частотали ғалаёнлар мавжудлигида, ишлаши учун кенгайтириш имкониятлари ўрганилган ва қўшимча шовқинлар фильтрига эга тегишлича баҳолаш схемаси таклиф этилган. Ўтказилган имитацион моделлаштириш натижалар, шиша эритиш печида паст частотали ғалаёнлар объектнинг киришиган таъсир қилиб, объектнинг ҳолатига ўз таъсирини ўтказади, деб ҳисоблаш имконини беради.*
Таянч сўзлар: *кузатувчи, Калман фильтри, имитацион моделлаштириш, математик модель, шиша эритиш печи.*

Аннотация: *Синтезируется модифицированный фильтр Калмана процесса варки стекла с учетом возмущений в виде последовательности цветных шумов. Изучена возможность расширения данного фильтра за счет фильтров шума для улучшения функционирования в присутствии низкочастотных возмущений и предложена соответствующая схема оценивания с дополнительными фильтрами шумов. Результаты проведенного имитационного моделирования позволяют считать, что низкочастотные возмущения в стекловаренной печи действуют на входе и влияют на состояние объекта управления.*
Ключевые слова: *наблюдатель, фильтр Калмана, имитационное моделирование, математическая модель, стекловарная печь.*

Introduction

The main technological process in glass production is glassmaking, the efficiency of which is determined by its temperature regime [1-4]. The temperature of the molten glass is the most important technological parameter that determines the processes of melting, cleaning, homogenization, re-cleaning and thermal homogeneity of glass. All necessitates the creation of a perfect system for monitoring and controlling the temperatures of the molten glass and the gaseous medium in the glass furnace.

An analysis of the systems for monitoring and controlling the temperature regime of a glass-melting furnace indicates that they provide for the measurement of temperatures at certain points of it [5-6]. The number of such points is very limited, which does not allow to form a complete picture of the temperature field of the glass furnace. This circumstance worsens control over the process and its diagnostics, which can lead to pre-emergency and even emergency situations. In addition, the efficiency of control systems based on a limited amount of information about the temperature field may be lower than possible. In this situation, an alternative is to use observers, in particular, the Kalman filter, which, on the basis of a mathematical model, makes it possible to estimate the temperature values at any point in the glass-making furnace using the measured input and output data. In practice, the difference between estimates and real measurements of the process takes place by the disturbance of the process, which causes model errors, on the one hand, and sensor inaccuracies (or their errors), on the other hand [7-11]. Over time, these differences can increase and lead to large inconsistencies between model predictions and real values of process variables. In this regard, in the development of control systems in the presence of disturbing influences, the development of the estimation procedure, in particular, the synthesis of observers using highly efficient filters [12] comes out on top.

Monitoring and control of the temperature regime of the glass making process

Let the differences$\mathcal{E}_y(t)$ between the real values $y(t)$ of the process parameters and the estimates of the models $\hat{y}(t)$ and be presented in the following form $\mathcal{E}_y(t) = y(t) - \hat{y}(t)$.
If the used mathematical model adequately describes the real glassmaking process, then the deviation of the predicted temperature values from the measured values can be considered caused by disturbances with known stochastic properties, then the observer can be synthesized by minimizing the mathematical expectation of the root-mean-square norm (RMS) error $\mathcal{E} = T - \hat{T}$ between the measured temperature field T and its estimate $\hat{T}$:

$$\|\mathcal{E}\|_{\text{СКН}} = (\lim_{k\to\infty} \text{E}\{\varepsilon^T(k)\varepsilon(k)\})^{1/2},$$

where $E\{\mathcal{E}^T(k)\mathcal{E}(k)\}$ is the mathematical expectation of the random variable $\mathcal{E}(k)$.

In this case, we will assume that the temperature measurements of the molten glass are performed periodically. The measurements at the k-moment of time of the values of y(t) are denoted as $y(k) = y(t_k) = y(k\Delta t)$.. In fig. 1 schematically shows the evaluation procedure. As you can see, two types of perturbations are considered: $d_1(k)$- perturbations that directly affect the state of the glass-making process and $d_2(k)$- perturbations that are observed in the initial measurements.

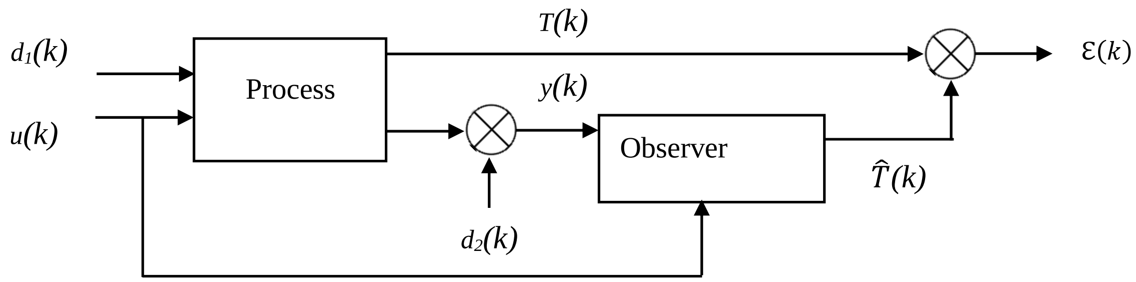

Fig. 1. ***Block diagram of the assessment procedure.***

When synthesizing the Kalman filter, the disturbances acting on the state of the process at intervals as signals of the "white noise" type [13]. However, in practice, there are disturbances that change slowly within the frequency of the process itself and significantly affect the process itself. An example of such slowly varying disturbances is the change in the redox number of the glass melt, which significantly affects the thermal conductivity of the latter. These disturbances are observed at the measured outputs. In this regard, the disturbance signals during the synthesis of the observer should be considered as a sequence of colored noise [14].

We are synthesizing an extended Kalman filter for the glassmaking process, taking into account disturbances in the form of a sequence of colored noise. This filter can be extended with noise filters to improve performance in the presence of low-frequency disturbances, which are no less important than high-frequency disturbances in the production of glass melting. In fig. 2 shows the estimation scheme by the Kalman filter with two noise filters *F1* and *F2*. Disturbances $d_1(k)$ and $d_2(k)$ are a sequence of colored noises that is formed as a result of filtering a sequence of white noises v_1 and v_2.

$$d_1 = F_1(q)v_1; \qquad d_2 = F_2(q)v_2,$$

where q - is the backward shift operator; (q) ∈ $R^{n_{d1}\times n_{d,1}}$ и $F_2(q) \in R^{n_{d,2}\times n_{d,2}}$ - are linear filters, signals v_1 and v_2 are independent and are normally

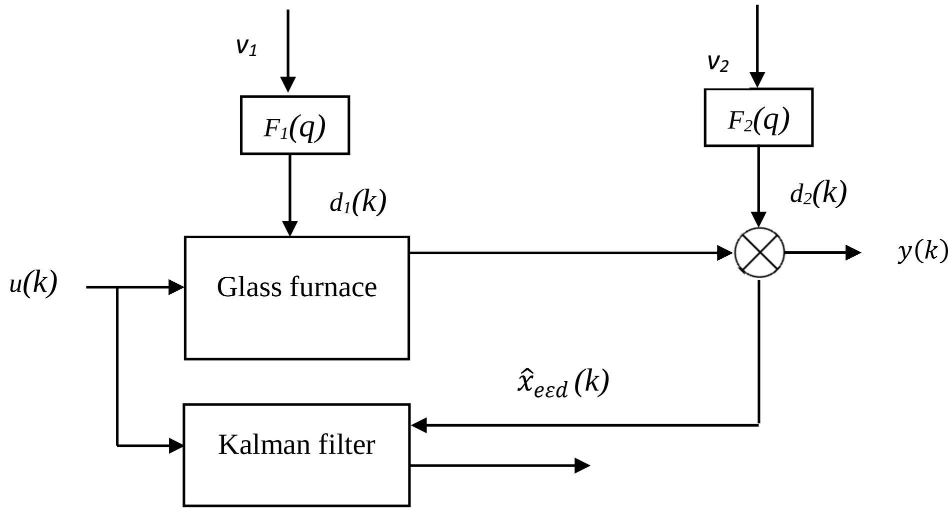

Fig. 2. ***Evaluation scheme by Kalman filter with two noise filters F1 and F2.***

The temperature deviation $\Delta T(K) = (T(K) - \bar{T})$ from the set operating point $\bar{T}$ and the measured outputs $y(k)$are calculated from the model

$$x(k+1) = Ax(k) + Bu(k) + G_1 d_1(k),$$
$$y(k) = C_y x(k) + G_2 d_2(k), \tag{1}$$
$$\Delta T(k) = C_T x(k)$$

with the state vector $R(k) \in R^{n_x}$ of the model, matrices of parameters $A \in R^{n_x \times n_x}$, $B \in R^{n_x \times n_u}$, $C_y \in R^{n_y \times n_x}$, $C_T \in R^{N \times n_x}$ and weight matrices G_1, G_2 of perturbations $d_1(k)$ and $d_2(k)$.

Elements of the matrices G_1, G_2 are selected on the basis of assumptions regarding the accuracy of the model, sensor noise and disturbances of the process itself.

In what follows, we assume that controls $u(k)$ and disturbances $d_1(k)$and $d_2(k)$ are independent, and the unknown initial state vector $x(0) = x_0$ - is a normally distributed random variable with an unknown covariance matrix $Q_0 x_0 \epsilon N(0, Q_0)$. Noise filters F_1 and F_2 can be represented by a state-space model

$$X_{F_1}(k+1) = A_{F_1} X_{F_1}(k) + B_{F_1} v_1$$
$$d_1(k) = C_{F_1} X_{F_1}(k) + D_{F_1} v_1, \tag{2}$$

$$X_{F_1}(k+1) = A_{F_2} X_{F_2}(k) + \underbrace{\begin{bmatrix} B_{F_2}^F & 0 \end{bmatrix}}_{B_{F_2}} \underbrace{\begin{bmatrix} v_2^F(k) \\ v_2^{NF}(k) \end{bmatrix}}_{v_2(k)},$$
$$X_2(k) = C_{F_2}(k) X_{F_2}(k) + \underbrace{\begin{bmatrix} 0 & D_{F_2}^{NF} \end{bmatrix}}_{D_{F_2}} \underbrace{\begin{bmatrix} v_2^F(k) \\ v_2^{NF}(k) \end{bmatrix}}_{v_2(k)}, \tag{3}$$

where $X_{F_1} \in R^{n_{d1}}$ $X_{F_2} \in R^{n_{d2}}$ - filter state variables, $A_{F_1} \in R^{n_{d1}\times n_{d1}}$, $B_{F_1} \in R^{n_{d1}\times n_{d1}}$, $C_{F_1} \in R^{n_{d1}\times n_{d1}}$, $D_{F_1} \in R^{n_{d1}\times n_{d1}}$, $A_{F_2} \in R^{n_{d2}\times n_{d2}}$, $B_{F_2} \in R^{n_{d2}\times n_{d2}}$, $C_{F_2} \in R^{n_{d2}\times n_{d2}}$, $B_{F_2}^F \in R^{n_{d2}\times n_{d2}}$, $C_{F_2} \in R^{n_{d2}\times n_{d2}}$, $D_{F_2}^F \in R^{n_{d2}\times n_{d2}}$ - matrices of parameters of models of two perturbation filters.

The disturbance vector ν₂ is split into two components: the vector v_2^F(k), which is filtered, and the vector v_2^{NF}(k), which is not filtered (white noise of the meters). It is believed that these vectors are independent of each other.

Model parameters are determined and are used to adjust the Kalman filter.

Substitute the mathematical description of filters (2) and (3) instead of $G_1 d_1(k)$ and $G_2 d_2(k)$ in equations (1):

$$\begin{bmatrix} X(k+1) \\ X_{F_1}(k+1) \\ X_{F_2}(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} A & C_{F_1} & 0 \\ 0 & A_{F_1} & 0 \\ 0 & 0 & A_{F_2} \end{bmatrix}}_{A^{(E)}} \underbrace{\begin{bmatrix} X(k) \\ X_{F_1}(k) \\ X_{F_2}(k) \end{bmatrix}}_{X^E(k)} + \underbrace{\begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix}}_{B^{(E)}} u(k) + \underbrace{\begin{bmatrix} D_{F_1} & 0 \\ B_{F_1} & 0 \\ 0 & B_{F_1} \end{bmatrix}}_{G_1^{(E)}} \underbrace{\begin{bmatrix} v_1(k) \\ v_2(k) \end{bmatrix}}_{d(k)}, \quad (4)$$

$$y(k) \underbrace{\begin{bmatrix} C & 0 & C_{F_2} \end{bmatrix}}_{C^{(E)}} \begin{bmatrix} X(k) \\ X_{F_1}(k) \\ X_{F_2}(k) \end{bmatrix} + Du(k) + \underbrace{\begin{bmatrix} 0 & D_{F_2} \end{bmatrix}}_{G_2^{(E)}} \begin{bmatrix} v_1(k) \\ v_2(k) \end{bmatrix}. \quad (5)$$

The mathematical model (4) and (5) can be written as

$$X^{(E)}(k+1) = A^{(E)} X^{(E)}(k) + B^{(E)} u(k) + G_1^{(E)} v^{(E)}(k), \quad (6)$$

$$y(k) = C^{(E)} X^{(E)}(k) + Du(k) + G_2^{(E)} v^{(E)}(k). \quad (7)$$

Further, the Kalman filter can be synthesized by known methods [15-17] using the matrices $A^{(E)}$ and $C^{(E)}$ to solve the Ricatti equations.

Consider four types of Kalman filters:

1. Standard filter: $C_{F_1} = 0$, $C_{F_2} = 0$, (ФК).

2. Modified Kalman filter with noise filters acting on the state of the object (ФКСО): $C_{F_1} = \begin{bmatrix} I_{n_y} & 0 \end{bmatrix}^T$, $C_{F_2} = 0$. In this case, it is assumed that the perturbations acting on the state of the object change slowly.

3. Modified filter with noise filters acting at the input of the object (ФКВ х О): $C_{F_1} = \begin{bmatrix} B^T & 0 \end{bmatrix}^T$, $C_{F_2} = 0$. In this case, the perturbations acting on the state of the object affect the same way as the input variables.

4. Modified filter with filters acting at the object output (ФКВ и О) $C_{F_1} = 0$, $C_{F_2} = I_{n_y}$. This case corresponds to slow changes in disturbances affecting the measurement of the output variables.

The purpose of the simulation is to investigate the effectiveness of the proposed modifications of the Kalman filter in comparison with a standard filter for evaluating temperatures at various points in the glass furnace. Six points were selected as control points located at the bottom of the glass furnace. The deviations $\Delta T(k)$ of the temperature of the roof of the glass-melting furnace from the set value and the flow rate of the molten glass S (k) are used as controls. To calculate the "measured" temperatures, a mathematical model was used in the form

$$x(k+1) = Ax(k) + Bu(k)$$
$$y(k) = C_y x(k) \quad (8)$$
$$T(k) = C_T x(k)$$

This model demonstrates the relationship of the temperature vector *T(k)* with the output vector *u(k)* ∈ R^2 and the measured temperature vector *y(k)* ∈ R^6. The state vector *x(k)* ∈ R^8 characterizes the memory of the model and has no direct physical meaning. The matrices $A \in R^{8x8}$, $A \in R^{8x2}$, $C_y \in R^{6x8}$ и $C_T \in R^{11628x8}$ are the matrices of the model parameters. Let us choose $A_{F_1} = I_{n_{d1}}$ и $A_{F_2} = I_{n_{d2}}$ as identity matrices. The matrices $B_{F_1} = \gamma_{d1_{Filt}} I_{n_{d1}}$ $B_{F_1}^F = \gamma_{d2_{Filt}} I_{n_{d1}}$ are the identity matrices multiplied by the weight coefficients $\gamma_{d1_{Filt}}$ and $\gamma_{d2_{Filt}}$. The matrices $D_{F_1} = \gamma_{d1} I_{n_{d1}}$ и $D_{F_2} = \gamma_{d2} I_{n_{d2}}$ are also chosen as unity, multiplied by the weight coefficients γ_{d1} and γ_{d2}.

During the simulation of the glass furnace, the reaction of the latter to the step input signals was investigated. A sequence of noise signals in the form of filtered white noise was added to the input signals, and white noise signals were added to the measured outputs.

Temperatures at all control points were estimated using the filters described above. Further, the error of the estimate $\varepsilon(k) = T(k) - \hat{T}(k)$ was analyzed. The results of the study show that the Kalman filter works quite efficiently when disturbances are applied to the inputs and act on the state of the control object.

Conclusion.

An observer of the state of the temperature regime of a glass-making furnace is synthesized in the form of a modification of the Kalman filter. Simulation modeling of the functioning of a glass-making furnace with observers was carried out, based on the results of which recommendations were determined on the advisability of using observers' data for various types of disturbances.

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