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Optimization of the Parameters of a Model Predictive Control System for an Industrial Fractionator

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Abstract—The problem of parametric synthesis of a model predictive control (MPC) system by the chemical process of production of the kerosene fraction of an industrial fractionator under conditions of constraints and uncertainty is considered. The optimal parameters of the MPC algorithm are obtained as a result of solving the problem of multi-criteria optimization, taking into account the intervally specified parameters of the plant model.

Keywords: model predictive control, robust control, multi-criteria optimization

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1. INTRODUCTION

Model predictive control (MPC) has recently developed a lot due to the fact that it has a number of significant advantages in solving the problems of control multidimensional industrial plants in the presence of constraints on control actions [1–3].

When finding the values of control actions at each time step k, the optimization problem is solved. The objective function using the predict of P forward time steps ($\tilde{y}_{k+j}$, $j = 1, \ldots, P$) is minimized by selecting the increment values of the control variables Δu on the control horizon M. The values of the control actions are determined by M ssteps forward, but only the first change is used Δu_k, i.e. at the current time. After u_k is executed, the measurement of the output variable comes in the next step y_{k+1} and the model error is corrected, since the measured value y_{k+1}, as a rule, does not coincide with the forecast value. For a multidimensional system consisting of controlled variables (CV) n_{CV} and manipulated variables (MV) n_{MV}, the matrix of the system dynamics is formed from the coefficients of the finite step response (FSR):

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_1 & 0 & \ldots & 0 \\ \mathbf{S}_2 & \mathbf{S}_1 & 0 & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \mathbf{S}_M & \mathbf{S}_{M-1} & \ldots & \mathbf{S}_1 \\ \mathbf{S}_{M+1} & \mathbf{S}_M & \ldots & \mathbf{S}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{S}_P & \mathbf{S}_{P-1} & \ldots & \mathbf{S}_{P-M+1} \end{bmatrix},$$

where $\mathbf{S}_i = \begin{bmatrix} S_{11,i} & S_{12,i} & \dots & S_{1n_{MV},i} \\ S_{21,i} & \dots & \dots & S_{2n_{MV},i} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n_{CV}1,i} & \dots & \dots & S_{n_{CV}n_{MV},i} \end{bmatrix}$ – matrix $n_{CV} \times n_{MV}$ of step response coefficients for the ith time step.

First-order transfer function with a delay are mainly used as initial data for predictive models in the form of an FSR:

$$F(s) = \frac{g}{\tau s + 1} e^{-\theta s}.$$

The parameters of the model for a multivariable system can be written as matrices:

$$\hat{\mathbf{G}} = \begin{pmatrix} \hat{g}_{1,1} & \dots & \hat{g}_{1,n_{MV}} \\ \vdots & \ddots & \vdots \\ \hat{g}_{n_{CV},1} & \dots & \hat{g}_{n_{CV},n_{MV}} \end{pmatrix}, \quad \hat{\mathbf{T}} = \begin{pmatrix} \hat{\tau}_{1,1} & \dots & \hat{\tau}_{1,n_{MV}} \\ \vdots & \ddots & \vdots \\ \hat{\tau}_{n_{CV},1} & \dots & \hat{\tau}_{n_{CV},n_{MV}} \end{pmatrix}, \quad \hat{\mathbf{\Theta}} = \begin{pmatrix} \hat{\theta}_{1,1} & \dots & \hat{\theta}_{1,n_{MV}} \\ \vdots & \ddots & \vdots \\ \hat{\theta}_{CV,1} & \dots & \theta_{n_{CV},n_{MV}} \end{pmatrix},$$

where $\hat{\mathbf{G}}$ is the matrix of the gain coefficients, $\hat{\mathbf{T}}$ is the matrix of the time constants, $\hat{\mathbf{\Theta}}$ is the matrix of the delay values.

The elements of the matrix $\mathbf{S}$ are formed on the basis of $\hat{\mathbf{G}}$, $\hat{\mathbf{T}}$ and $\hat{\mathbf{\Theta}}$:

$$\begin{cases} \mathbf{S}_i = 0, & i\Delta t \leqslant \hat{\mathbf{\Theta}} \\ \mathbf{S}_i = \hat{\mathbf{G}} \left(1 - e^{\frac{-\left(i\Delta t - \hat{\mathbf{\Theta}}\right)}{\hat{\mathbf{T}}}} \right), & i\Delta t > \hat{\mathbf{\Theta}}. \end{cases}$$

The control problem can be formulated as an optimization problem with the following objective function [4]:

$$\min_{\Delta \mathbf{U}_k} \mathbf{J} = \hat{\mathbf{E}}_{k+1}^{\mathrm{T}} \mathbf{Q} \hat{\mathbf{E}}_{k+1} + \Delta \mathbf{U}_k^{\mathrm{T}} \mathbf{R} \Delta \mathbf{U}_k$$

s.t.

$$\mathbf{y}_{k+j}^{-} \leqslant \tilde{\mathbf{y}}_{k+j} \leqslant \mathbf{y}_{k+j}^{+} \quad (j = 1, \dots, P),$$
$$\mathbf{u}^{-} \leqslant \mathbf{u}_{k+j} \leqslant \mathbf{u}^{+} \quad (j = 0, 1, \dots, M-1),$$
$$\Delta \mathbf{u}^{-} \leqslant \Delta \mathbf{u}_{k+j} \leqslant \Delta \mathbf{u}^{+} \quad (j = 0, 1, \dots, M-1),$$

where $\mathbf{u}_k = \left[u_{1|k}, \dots, u_{n_{MV}|k}\right]^{\mathrm{T}}$ is a vector of MV values at time k; $\Delta \mathbf{U}_k = [\Delta \mathbf{u}_k, \dots, \Delta \mathbf{u}_{k+M-1}]$ is a matrix M of changes in MV values at time k ($\Delta \mathbf{u}_k = \left[\Delta u_{1|k}, \dots, \Delta u_{n_{MV}|k}\right]^{\mathrm{T}}$); $\tilde{\mathbf{y}}_{k+j} = \left[\tilde{y}_{1|k+j}, \dots, \tilde{y}_{n_{CV}|k+j}\right]^{\mathrm{T}}$ is a vector of corrected predicted CV values at time $k+j$; $\mathbf{Q}$ and $\mathbf{R}$ are diagonal weight matrices for prioritizing elements $\hat{\mathbf{E}}_{k+1}$ and controlling changes $\Delta \mathbf{U}_k$, respectively.

The predictable error vector $\hat{\mathbf{E}}_{k+1}$ is defined as

$$\hat{\mathbf{E}}_{k+1} = \mathbf{Y}_{k+1}^{ref} - \tilde{\mathbf{Y}}_{k+1},$$

where $\mathbf{Y}_{k+1}^{ref}$ is the vector of given CV values at time $k+1$, $\tilde{\mathbf{Y}}_{k+1}$ is the vector of corrected predicted values:

$$\tilde{\mathbf{Y}}_{k+1} = \mathbf{S} \Delta \mathbf{U}_k + \hat{\mathbf{Y}}_{k+1}^{o} + [\mathbf{y}_k - \hat{\mathbf{y}}_k],$$

where $\hat{\mathbf{Y}}_{k+1}^{o} = \sum_{i=1}^{N-2} \mathbf{S}_{i+1} \Delta \mathbf{u}_{k-i} + \mathbf{S}_N \mathbf{u}_{k-N+1}$ is the vector of forecasts of unforced responses.

This paper considers the MPC algorithm, in which the increments of control actions (MV) are determined analytically [5]:

$$\Delta \mathbf{U}(k) = \mathbf{K}_C \hat{\mathbf{E}}^o(k+1),$$

where $\hat{\mathbf{E}}^o(k+1)$ is the predicted deviations from the initial trajectory with the constancy of the values of future control actions; $\mathbf{K}_C$ is the matrix of the regulator gain, which is calculated as $\mathbf{K}_C = \left(\mathbf{S}^{\mathrm{T}}\mathbf{Q}\mathbf{S} + \mathbf{R}\right)^{-1}\mathbf{S}^{\mathrm{T}}\mathbf{Q}$.

In spite of its advantages, MPC depends on the accuracy of the model, and transients in the control system can deteriorate in the presence of uncertainty, perturbations, and model errors (mismatch of the MPC model with the model of the controlled plant) [6]. In the existing works, in order to compensate for the uncertainty, it is proposed to introduce output predictors into the structure of the control system for various parameters of the plant (family of plants) [7, 8], which increases the complexity of the control system in the case of multidimensional plants, and the number of required computing resources of the MPC algorithm for finding a sequence of optimal increments of control actions increases significantly. In contrast to the known works, in this paper, it is proposed to take into account the uncertainty of the plant at the design stage of the MPC algorithm, i.e. to search for the optimal parameters of the regulator based on the predictive model (weight matrices $\mathbf{Q}$ and $\mathbf{R}$), when the parameters of the plant are set intervally.

2. DESCRIPTION OF THE PROCESS UNIT AND FORMULATION OF THE PROBLEM

A fractionation column C-2 is considered (Fig. 1), in which a multicomponent hydrocarbon crude mixture is divided into naphta, kerosene, and other fractions. Column C-2 has an additional side stripping column—a column for stripping the C-3 kerosene fraction. Column C-2 contains 44 valve trays in the rectification section and 12 valve trays in the stripping section. Excess heat in the column is removed by bottom pumparound (BPA). The top temperature (TIC1) is controlled by the supply of reflux in the upper part of the C-2 fractionator. The purpose of column C-3 is the stripping of light hydrocarbons from the kerosene fraction due to the heat of the BPA of column C-2 supplied to the reboiler E-2. Light hydrocarbon vapors from column C-3 are returned to column C-2. The temperature of the product kerosene at the outlet of column C-3 is controlled by the TIC2 loop. The plant in question has $n_{CV} = 2$ and $n_{MV} = 2$. The matrix of transfer

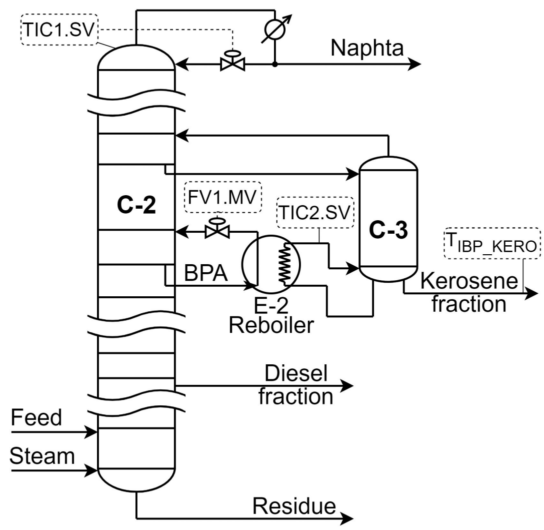

Fig. 1. Process unit block diagram.

Table 1. Transfer matrix of the plant

	Top temperature C-2 (TIC1.SV)	Bottom temperature C-3 (TIC2.SV)
$T_{\text{IBP\_KERO}}$	$F_{1,1} = \dfrac{g_{1,1}}{\tau_{1,1}s+1}e^{-\theta_{1,1}s}$	$F_{1,1} = \dfrac{g_{1,2}}{\tau_{1,2}s+1}e^{-\theta_{1,2}s}$
FV1.MV % of valve opening E-2	$F_{2,1} = \dfrac{g_{2,1}}{\tau_{2,1}s+1}e^{-\theta_{2,1}s}$	$F_{2,2} = \dfrac{g_{2,2}}{\tau_{2,2}s+1}e^{-\theta_{2,2}s}$

functions of the plant is presented in Table 1. Transfer functions are aperiodic links of the 1st order with a delay.

The control task is to maintain the initial boiling point of the kerosene fraction ($T_{\text{IBP\_KERO}}$) within a set range.

3. DETERMINATION OF THE OPTIMAL PARAMETERS OF THE REGULATOR BASED ON THE PREDICTIVE MODEL FOR QUALITY CONTROL OF THE INDUSTRIAL FRACTIONATOR PRODUCT

Let us denote the parameters of the transfer functions of the plant in the form of the following matrices:

$$\mathbf{G} = \begin{pmatrix} g_{1,1} & g_{1,2} \\ g_{2,1} & g_{2,2} \end{pmatrix}, \quad \mathbf{T} = \begin{pmatrix} \tau_{1,1} & \tau_{1,2} \\ \tau_{2,1} & \tau_{2,2} \end{pmatrix}, \quad \boldsymbol{\Theta} = \begin{pmatrix} \theta_{1,1} & \theta_{1,2} \\ \theta_{2,1} & \theta_{2,2} \end{pmatrix}.$$

Matrices of parameters of the transfer functions of the regulator (to find the FSR):

$$\hat{\mathbf{G}} = \begin{pmatrix} \hat{g}_{1,1} & \hat{g}_{1,2} \\ \hat{g}_{2,1} & \hat{g}_{2,2} \end{pmatrix}, \quad \hat{\mathbf{T}} = \begin{pmatrix} \hat{\tau}_{1,1} & \hat{\tau}_{1,2} \\ \hat{\tau}_{2,1} & \hat{\tau}_{2,2} \end{pmatrix}, \quad \hat{\boldsymbol{\Theta}} = \begin{pmatrix} \hat{\theta}_{1,1} & \hat{\theta}_{1,2} \\ \hat{\theta}_{2,1} & \hat{\theta}_{2,2} \end{pmatrix}.$$

Set the upper and lower limits of the parameter ranges:

$$\overline{\mathbf{G}} = \begin{pmatrix} 0.2 & 0.9 \\ -0.5 & 0.9 \end{pmatrix}, \quad \overline{\mathbf{T}} = \begin{pmatrix} 18 & 18 \\ 20 & 14 \end{pmatrix}, \quad \overline{\boldsymbol{\Theta}} = \begin{pmatrix} 8 & 7 \\ 9 & 7 \end{pmatrix},$$

$$\underline{\mathbf{G}} = \begin{pmatrix} 0.1 & 0.5 \\ -1 & 0.45 \end{pmatrix}, \quad \underline{\mathbf{T}} = \begin{pmatrix} 6 & 6 \\ 8 & 6 \end{pmatrix}, \quad \underline{\boldsymbol{\Theta}} = \begin{pmatrix} 2 & 3 \\ 1 & 1 \end{pmatrix}.$$

Let us assume that the actual parameters of the transfer functions of the plant lie in the middle of the specified range:

$$\mathbf{G} = \frac{\overline{\mathbf{G}} + \underline{\mathbf{G}}}{2} = \begin{pmatrix} 0.15 & 0.7 \\ -0.75 & 0.675 \end{pmatrix}, \quad \mathbf{T} = \frac{\overline{\mathbf{T}} + \underline{\mathbf{T}}}{2} = \begin{pmatrix} 12 & 12 \\ 14 & 10 \end{pmatrix}, \quad \boldsymbol{\Theta} = \frac{\overline{\boldsymbol{\Theta}} + \underline{\boldsymbol{\Theta}}}{2} = \begin{pmatrix} 5 & 4 \\ 6 & 4 \end{pmatrix}.$$

To study the transient processes in the control system, we set the vector of tasks by CV $\mathbf{r} = [r_1 \quad r_2] = [1 \quad 0.8]$. The adjusting parameters of the regulator are the matrix of weights by error CV $\mathbf{Q} = \operatorname{diag}\{Q_1, Q_2\}$ and the matrix of weights by increment MV $\mathbf{R} = \operatorname{diag}\{R_1, R_2\}$. In the course of the study, it was established that the quality of regulation depended not so much on the values of the weights $\mathbf{Q}$ and $\mathbf{R}$ as on the ratio of the weights relative to each other. Therefore, within the framework of this study, the weights $\mathbf{Q} = \operatorname{diag}\{Q_1, Q_2\}$ are set.

As a criterion for the accuracy of control tasks according to CV, the mean square error relative to the desired dynamics was chosen [9]:

$$J = \sum_{i=1}^{N_M} \sum_{q=1}^{n_{CV}} \left(y_{i,q}^{ref} - y_{i,q} \right)^2,$$

where $y_{i,q}^{ref}$ is the value of the desired trajectory q CV at the ith time point, $y_{i,q}$ is the actual value of q CV at the ith time point.

Thus, the optimization problem can be written as:

$$\min_{\mathbf{R}>0} J = \sum_{i=1}^{N_M} \sum_{q=1}^{n_{CV}} \left(y_{i,q}^{ref} - y_{i,q} \right)^2 ,$$

where $\mathbf{R} > 0$ means that all diagonal elements are positive. The calculation of the desired trajectory is made according to the following expression:

$$y_{i,q}^{ref} = \frac{\mathbf{r}_q \sum_{j=1}^{n_{MV}} \mathbf{G}_{q,j} \left(1 - e^{\frac{\tilde{t}}{\mathbf{T}_{q,j}}} \right)}{\sum_{j=1}^{n_{MV}} \left| \mathbf{G}_{q,j} \right|}, \qquad \tilde{t} = \begin{cases} i - \mathbf{\Theta}_{q,j}, & i \geqslant \mathbf{\Theta}_{q,j} \\ 0, & i < \mathbf{\Theta}_{q,j}, \end{cases}$$

where $i = 1, \ldots, N_M$ are the time points, and $q = 1, \ldots, n_{CV}$ is the CV number for which the desired trajectory is calculated. The purpose of this study is to find such values of the weights $\mathbf{R} = \operatorname{diag}\{R_1, R_2\}$ that the output variables of the plant are as close as possible to the desired dynamics for various parameters $\hat{\mathbf{G}}$, $\hat{\mathbf{T}}$ and $\hat{\mathbf{\Theta}}$, lying within the specified range.

To determine the robust optimal values of $\mathbf{R}$, consider cases where one of the parameters $\hat{\mathbf{G}}$, $\hat{\mathbf{T}}$ and $\hat{\mathbf{\Theta}}$ lies at the boundary of the ranges, and the rest are in the middle. The cases under consideration are presented in Table 2.

Table 2. Controller model parameter variations

Index $\tilde{\mathbf{p}}$	Parameter value			Index $\tilde{\mathbf{p}}$	Parameter value		
	$\hat{\mathbf{G}}$	$\hat{\mathbf{T}}$	$\hat{\mathbf{\Theta}}$		$\hat{\mathbf{G}}$	$\hat{\mathbf{T}}$	$\hat{\mathbf{\Theta}}$
1	$\underline{\mathbf{G}}$	$\mathbf{T}$	$\mathbf{\Theta}$	4	$\mathbf{G}$	$\overline{\mathbf{T}}$	$\mathbf{\Theta}$
2	$\overline{\mathbf{G}}$	$\mathbf{T}$	$\mathbf{\Theta}$	5	$\mathbf{G}$	$\mathbf{T}$	$\underline{\mathbf{\Theta}}$
3	$\mathbf{G}$	$\underline{\mathbf{T}}$	$\mathbf{\Theta}$	6	$\mathbf{G}$	$\mathbf{T}$	$\overline{\mathbf{\Theta}}$

The optimization problem in a general form for each of the cases under consideration can be represented as:

$$\min_{\mathbf{R}>0} J^{\tilde{\mathbf{p}}} = \sum_{i=1}^{N_M} \sum_{q=1}^{n_{CV}} \left(y_{i,q}^{ref} - \left(y_{i-1,q} + \mathbf{S}_i^{\tilde{\mathbf{p}}} \left(\mathbf{S}_i^{\tilde{\mathbf{p}}\mathrm{T}} \mathbf{Q} \mathbf{S}_i^{\tilde{\mathbf{p}}} + \mathbf{R} \right)^{-1} \mathbf{S}_i^{\tilde{\mathbf{p}}\mathrm{T}} \mathbf{Q} \hat{\mathbf{E}}^o (k+1) \right) \right)^2 ,$$

where $\begin{cases} \mathbf{S}_i^{\tilde{\mathbf{p}}} = 0, & i\Delta t \leqslant \hat{\mathbf{\Theta}}^{\tilde{\mathbf{p}}} \\ \mathbf{S}_i^{\tilde{\mathbf{p}}} = \hat{\mathbf{G}}^{\tilde{\mathbf{p}}} \left(1 - e^{-\frac{i\Delta t - \hat{\mathbf{\Theta}}^{\tilde{\mathbf{p}}}}{\hat{\mathbf{T}}^{\tilde{\mathbf{p}}}}} \right), & i\Delta t > \hat{\mathbf{\Theta}}^{\tilde{\mathbf{p}}}. \end{cases}$

To determine the optimal (in this case, robust) parameters of the MPC algorithm, we will vary the values $\mathbf{R} = \operatorname{diag}\{R_1, R_2\}$ in the range $0.1 \leqslant R_1 \leqslant 35$ and $0.1 \leqslant R_2 \leqslant 40$ in increments of 0.2. The graphs in Fig. 2 show the surfaces of the change in the accuracy criterion. Table 3 shows the weights $\mathbf{R}$ at which the criteria values $J^{\tilde{\mathbf{p}}}$ are minimal.

Table 3. Optimal values of $\mathbf{R}$ for different criteria $J^{\tilde{\mathbf{p}}}$

	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=1}$	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=2}$	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=3}$	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=4}$	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=5}$	$\mathbf{R}_{opt}^{\tilde{\mathbf{p}}=6}$
R_1	0.1	0.7	6.9	2.5	8.9	0.1
R_2	32.9	1.1	28.5	12.1	32.9	3.5

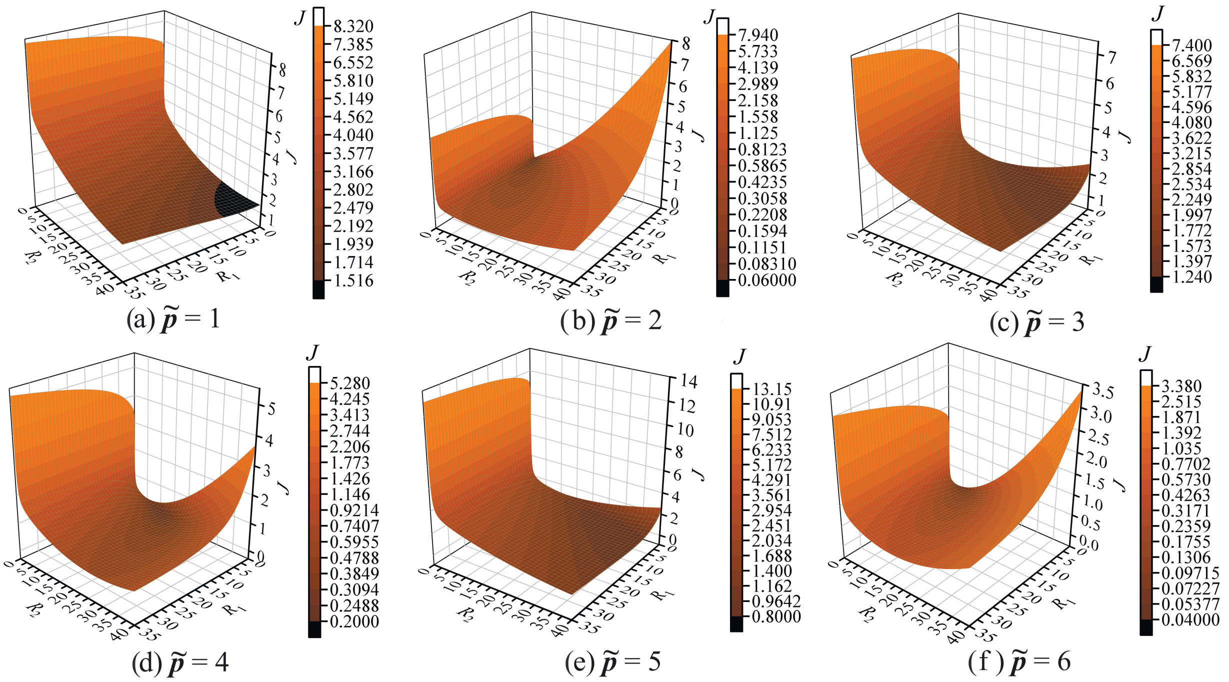

Fig. 2. Criteria values $J^{\tilde{\mathbf{p}}}$ for different R_1 and R_2.

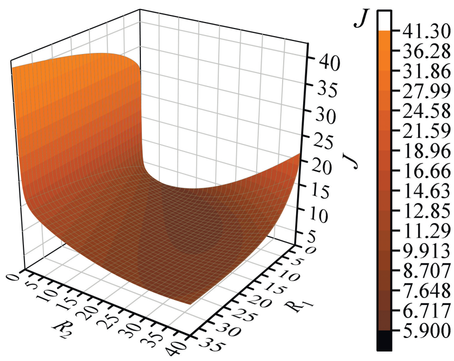

Fig. 3. Change of $\breve{J}$ at different values R_1 and R_2.

Due to the fact that the optimal values of the weight matrix $\mathbf{R}$ are different for the 6 cases under consideration, we will use the convolution of criteria [10] to find the robust optimal parameters:

$$\breve{J} = \sum_{\tilde{\mathbf{p}}=1}^{6} w^{\tilde{\mathbf{p}}} \times J^{\tilde{\mathbf{p}}}.$$

Since the values of the criteria for the cases under consideration have the same physical dimension, we assume that the value of $w^{\tilde{\mathbf{p}}} = 1$, $\tilde{\mathbf{p}} = 1, \ldots, 6$. Figure 3 shows the surface of change $\breve{J}$ when the values of R_1 and R_2 change. The values of the weights $\mathbf{R}$ corresponding to the minimum value of the criterion $\breve{J}$ are equal to $\mathbf{R}_{opt}^{\breve{J}} = \operatorname{diag}\{5.3, 17.1\}$.

Figure 4 presents the optimal values of $\mathbf{R}$ in the plane R_1R_2. Figure 5 shows the CV transients when the values of $\mathbf{R} = \mathbf{R}_{opt}^{\tilde{\mathbf{p}}=1}$ and $\mathbf{R} = \mathbf{R}_{opt}^{\breve{J}}$.

It can be concluded from the graphs in Fig. 5 that the use of weights $\mathbf{R}$ selected on the basis of $\breve{J}$, i.e. taking into account the variations in the parameters of the object, makes it possible to

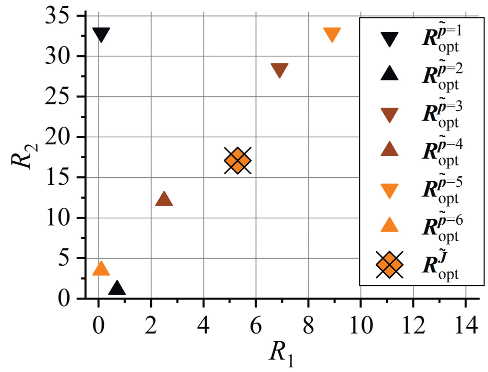

Fig. 4. Location of optimal values of **R**.

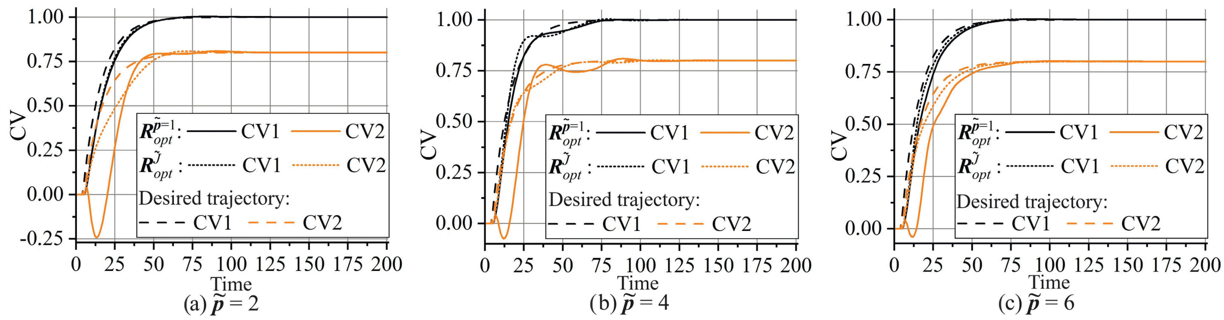

Fig. 5. CV transients at $\mathbf{R} = \mathbf{R}_{opt}^{\tilde{\mathrm{p}}=1}$ and $\mathbf{R} = \mathbf{R}_{opt}^{\breve{J}}$.

reduce the deviation from the desired trajectory in comparison with the case when the optimal weights are selected on the basis of only one of the criteria $J^{\tilde{\mathrm{p}}}$, i.e. without taking into account the uncertainty of the parameters of the plant.

Table 4. Values of criteria $J^{\tilde{\mathrm{p}}}$ (deviation from the desired dynamics) for different **R**

	R_1	R_2	$\tilde{\mathrm{p}} = 1$	$\tilde{\mathrm{p}} = 2$	$\tilde{\mathrm{p}} = 3$	$\tilde{\mathrm{p}} = 4$	$\tilde{\mathrm{p}} = 5$	$\tilde{\mathrm{p}} = 6$
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=1}$	0.1	32.9	1.34848	6.06283	2.00167	2.62597	2.03054	2.39714
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=2}$	0.7	1.1	3.7571	0.06194	2.29674	0.73448	2.6284	0.18394
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=3}$	6.9	28.5	1.59663	1.89024	1.25891	0.64345	0.82054	0.90192
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=4}$	2.5	12.1	2.38149	0.71668	1.44793	0.21418	1.2088	0.15819
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=5}$	8.9	32.9	1.54609	2.1035	1.26915	0.82553	0.80598	1.13606
$\mathbf{R}_{opt}^{\tilde{\mathrm{p}}=6}$	0.1	3.5	2.97203	0.43404	1.54271	0.3417	1.48232	0.04001
$\mathbf{R}_{opt}^{\breve{J}}$	5.3	17.1	1.94841	0.87779	1.38022	0.2607	1.05938	0.28966

4. CONCLUSION

In the framework of this work, a search was made for the robust optimal values of the weights **R** for the control system based on the predictive model, taking into account the parametric uncertainty of the parameters of the control plant. The optimal weights were found for cases where one of the parameters is at the boundary of the range, and the rest are in the middle. With the help of convolution of criteria, robustly optimal values $\mathbf{R}_{opt}^{\breve{J}} = \mathrm{diag}\,\{5.3, 17.1\}$ were found that ensure the best quality of control of the $\mathrm{T_{IBP\_KERO}}$ of kerosene fraction of the industrial fractionator. It is shown that the use of $\mathbf{R}_{opt}^{\check{J}}$ made it possible to reduce the deviation from the desired dynamics in comparison with the use of the optimal value of $\mathbf{R}$ without taking into account the uncertainty.

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