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Integrating virtual analyzers as part of improved control systems for technological processes

Yo'ldoshev Otabek

Abstract:

The work reflects the current state of oil production technology and identifies trends in its improvement and further development in an industrial automation environment using modern distributed monitoring methods, building control and management systems for mass-exchange technological processes of multi-component rectification..

Keywords: multi-component rectification regimes, mass-exchange technological processes control and management, predictive model control, virtual analyzers.

The current state of multi-component rectification production technology

The management strategy based on the predictive model (Model Predictive Control - MRS) involves taking into account the future behavior of the object, which, under conditions of controlled influence and controlled technological variables, allows for an improvement in the quality of regulation [1, 2). Manipulated variables (*MV*) are those that are usually controlled by operators, such as the flow rate of sharp irrigation, the pressure of the fuel gas on the furnace, and the rotation of the compressor turbine. Controlled variables (*CV*) are dependent parameters of the TP, i.e. variables dependent on the *MV*. These include: (1) the ones that are included in the optimization task, for example, the top temperature of the column, the position of the regulating valve, the pressure difference in the column; (2) product specifications, such as kerosene flash point, polyethylene melt flow rate. Raw material composition and temperature can be considered as perturbed variables (DV), i.e., those measured variables that are not regulated in the control process, but influence the values of the regulated variables.

The control scheme with a predictive model is shown in Fig. 1.1.

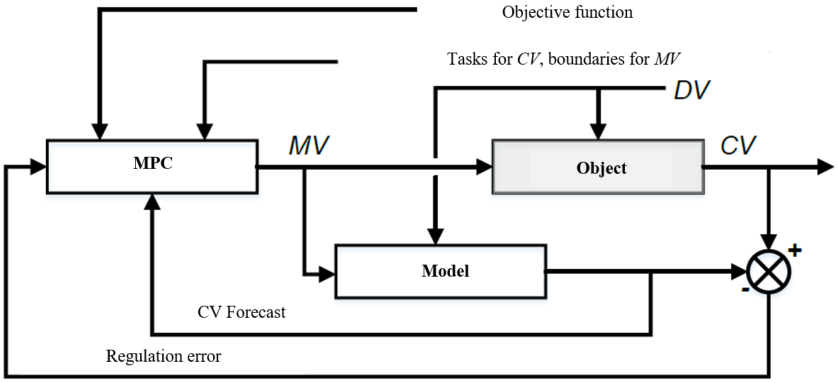

Figure 1.1 – Scheme of a control system with a predictive model

A forecast of the future behavior of the *CV* as a function of future values of the *MV* and measured *DV* is constructed using models of the object that relate the controlled variables of the *CV* to the manipulated *MV* and perturbed *DV*. Future values of *MV* are selected so as to achieve the optimal value of the criterion while observing the restrictions on *CV* and *MV*. The criterion may be the minimum cost or energy consumption, maximum productivity, etc., achieved in the interval of the forecast of the object's behavior. To build a dynamic model, the setup is tested for stepwise impacts, during which *MVs* are subjected to training stepwise impacts, *DVs* and corresponding *CV* responses are measured. The data obtained during the tests are processed and the parameters of the models are determined.

The forecast of the future behavior of CV as a function of future values of MV and measured DV is constructed using control-related variables CV, manipulated MV, and disturbance DV models of the object. Future values of MV are chosen to achieve an optimal value of the criterion while observing the constraints on CV and MV. The criterion may include minimizing cost or energy consumption, maximizing productivity, etc., achievable within the interval of the object's behavior prediction.

For constructing the dynamic model, experiments are conducted on a test setup where the object is subjected to step disturbances. The measured CV responses during these disturbances are processed and analyzed to determine the model parameters. The data obtained during the tests form the basis for modeling the object.

To predict the behavior of controlled variables, a complete process model is used, which consists of a matrix of dynamic sub-models. Each sub-model describes the influence of one of the manipulated variables (MV) or disturbances (DV) on one of the controlled variables (CV). A sub-model describes how the influence of an independent variable on the controlled variable changes over time, i.e., it reflects the dynamic response of the controlled variable. If the independent variable does not affect the controlled variable, the sub-model is equal to zero.

To obtain the models, it is necessary to:

Collect the dynamic responses of all controlled variables to each manipulated input and to each disturbance;

Conduct the identification procedure.

Before performing object tests, it is necessary to determine how and to what extent the controlled variables change in response to changes in the manipulated and disturbance variables, i.e., the influence parameter matrix.

$$\min_{x,y} \left\| \boldsymbol{W} \left(\boldsymbol{A}x - y \right) \right\|^2 + x^{\mathrm{T}} \Lambda x \,,$$

$$\min_{x,y} \left\| \begin{pmatrix} W & & \\ & W_p & \\ & & W_0 \end{pmatrix} \left(\begin{bmatrix} A \\ A_p \\ S_1 \end{bmatrix} x - \begin{bmatrix} y \\ y_p \\ x_{ss} \end{bmatrix} \right) \right\|^2 + x^{\mathrm{T}} \Lambda x \,,$$

$$y_{\mathrm{lo}} \le y \le y_{\mathrm{hi}} \,,$$

$$y_{\mathrm{p_{lo}}} \le y_p \le y_{\mathrm{p_{hi}}} \,,$$

$$x_{\mathrm{lo}} \le x \le x_{\mathrm{hi}} \,,$$

$$\mathrm{mv}_{\mathrm{lo}} \le \boldsymbol{S}x \le \mathrm{mv}_{\mathrm{hi}} \,,$$

$$\boldsymbol{S} = \begin{bmatrix} 1 & & & & & & & & & 0 \\ \vdots & \ddots & & & & & & & & \\ 1 & \cdots & 1 & & & & & & & \\ & & & 1 & & & & & & \\ & & & \vdots & \ddots & & & & & \\ & & & 1 & \cdots & 1 & & & & \\ & & & & & & \ddots & & & \\ & & & & & & & 1 & & \\ & & & & & & & \vdots & \ddots & \\ 0 & & & & & & & 1 & \cdots & 1 \end{bmatrix}$$

$$S_1 = \begin{bmatrix} 1 & \cdots & 1 & & & & & & & \\ & & & 1 & \cdots & 1 & & & & \\ & & & & & & \ddots & & & \\ & & & & & & & 1 & \cdots & 1 \end{bmatrix},$$

Where:

A – dynamic model matrix (response to a unit step);

W – diagonal weight matrix;

S – matrix with cumulative sum;

S_1 – summation matrix;

y_0, y_{hi} – upper and lower boundaries of y;

y_{r0}, y_{rhi} – upper and lower boundaries for forming the manipulated control;

x_o, x_{hi} – upper and lower boundaries of the control step increment array;

mv_o, mv_{hi} – upper and lower boundaries of MV;

$x^T\Lambda x$ – penalty variable.

For continuous chemical-technological processes of the Honeywell type, the Robust Multivariable Predictive Control Technology (RMPCT) or the Profit® Controller is used. The Profit® Controller module is applied in APC systems in combination with traditional advanced regulatory methods [143].

The optimization criterion for the MPC-controller Profit® Controller developed by Honeywell Corporation is described as follows [144]:

$$I = \sum_{j=1}^{\infty}\left(\left\|CV_j - CV_0\right\|_Q^2 + \left\|MV_j - MV_0\right\|_R^2\right),$$

Where:

CV_0 and MV_0 – setpoints of controlled and manipulated variables in the steady-state mode;

CV and MV – expected values of controlled and manipulated variables;

$\|x\|_2^2 = x^TQx$ – norm;

Q and R – matrices of weighting coefficients.

The optimization of the control process can also be carried out according to the techno-economic criterion:

$J = \sum_i b_i CV_i + \sum_i a_i^2 (CV_i - CV_{0i})^2 + \sum_j b_j MV_j + \sum_j a_j^2 (MV_j - MV_{0j})^2$, (2.3)

Where:

b_i and a_i – linear and quadratic coefficients for CV_i;

b_j and a_j – linear and quadratic coefficients for MV_j.

The structural diagram of the integration of VA and MPC, forming the control system of the production process of MTBЭ, is presented in Figure 2.1

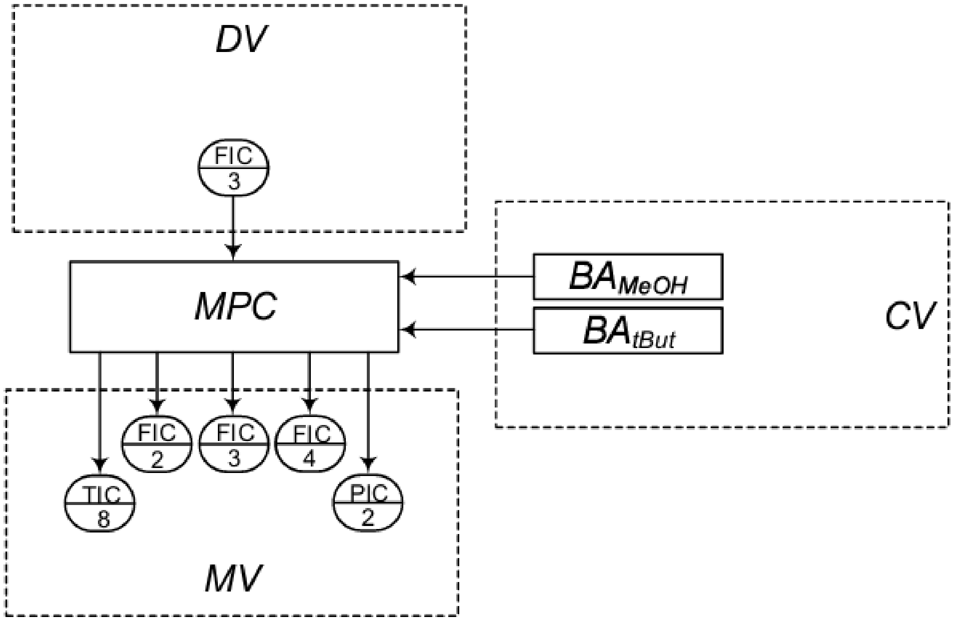

Figure 2.1 Integration of VA and CS TP

Conclusion

The analysis of the results of applying modern regression methods for building virtual analyzer (VA) models of quality indicators for mass transfer processes in distillation columns operating under extreme conditions allows us to draw the following conclusions: When constructing VA models of the output quality of distillation columns (DC) based on the proportion of isopentane and the content of benzene-forming components, multicollinearity of the inputs can be addressed using ridge regression. The algorithm ACE, based on nonlinear transformations of input variables, provides a more accurate model on the training dataset, as the physicochemical processes occurring in DCs are inherently nonlinear. However, the ACE algorithm performed worse than ridge regression on the generalization dataset due to the ACE algorithm's high sensitivity to the range of variables in the training dataset. When selecting the optimal number of input variables, it is advisable to use various methods for building VA models, relying on their informativeness in terms of physical meaning, especially under conditions of small datasets.

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