Model predictive control of a distillation column based on a MIMO model

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Abstract: The article discusses the application of model-based predictive control (MPC) using a multi-input, multi-output (MIMO) model to control a distillation process. It is shown that the MPC approach effectively accounts for the multi-connectivity of the distillation column's process variables, constraints on control actions, and disturbances, ensuring improved control quality and process energy efficiency.

Keywords: distillation column, MPC controller, MIMO model, optimal control, mass transfer processes

1. Introduction

Distillation processes are key in the chemical, petrochemical, and food industries and are characterized by high energy consumption, nonlinearity, and significant interdependencies among parameters. The quality of separation in a distillation column is determined by such factors as the purity of the distillate and bottoms product, thermal energy consumption, and operational stability under disturbances [1].

Traditional control systems based on PID controllers are generally ineffective for complex systems, such as distillation columns. Therefore, the development and application of improved control algorithms, such as model-based predictive control (MPC), is a pressing issue [2,5].

2. Features of the controlled object - the distillation column

The distillation column is a complex dynamic object with the following characteristic features:

- the presence of multiple input and output variables;
- strong cross-talk between control channels;
- significant time delays;
- nonlinearity of characteristics and variability of parameters;
- the presence of technological and operational limitations.

The main control variables include reflux flow rate, still heat load, feed flow rate, and column pressure. Output variables typically include concentrations of key components in the distillate and still product, liquid level, and the temperature profile along the column [3,4].

3. MIMO model of a distillation column

To adequately describe the dynamics of a distillation column, a MIMO model is used, which takes into account the influence of multiple inputs on a set of output variables. In general, a linear dynamic model can be represented in state space:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ed(t),$$

$$y(t) = Cx(t)$$

where x(t) is the state vector, u(t) is the vector of control actions, d(t) is the vector of disturbances, y(t) is the vector of output variables, A, B, C, E are matrices of the corresponding sizes.

The model parameters can be obtained on the basis of material and heat balance equations with subsequent linearization in the vicinity of the operating mode or by identification methods based on experimental data [5-7].

4. Principles of MPC management

The MPC controller generates a control action by solving an optimization problem at each control step using a plant model. The main elements of the MPC are:

Relationship of predictive MIMO model with MPC objective function

A predictive MIMO model of a distillation column forms the basis for the MPC objective function and is used to forecast the behavior of output process parameters over a finite prediction horizon. At each control step, the current state of the object is substituted into the discrete model.

$$x(k+1)= A_d x\ (k)+ B_d u\ (k)+ E_d d\ (k),$$
$$y\ (k) = C_d x\ (k)$$

on the basis of which the predicted values of the output variables $y(\ k+i\ )\ ,\ i=1,\ldots,\ Np$ are calculated.

The resulting forecasts directly feed into the first part of the MPC objective function and reflect the expected deviations of key component concentrations, temperature levels, and liquid levels from specified setpoints . This ensures an explicit link between the distillation column dynamics described by the MIMO model and the control performance criterion.

The weight matrix Q allows for consideration of the varying process significance of output variables, such as prioritizing maintaining a specified distillate concentration over temperature parameters. The second component of the objective function, dependent on the increments of control actions $\Delta u\ (k)$, is formed taking into account the predicted plant response and aims to limit sudden changes in reflux flow rates, heat load, and other control signals, thereby improving the energy efficiency and resource effectiveness of the process.

Thus, the MPC optimization problem consists of finding a sequence of control actions that, given the constraints and multi-connected dynamics defined by the predictive MIMO model, minimizes the performance functional. This ensures coordinated multi-channel control of the distillation column and effective disturbance suppression under complex process dynamics[8-10].

The optimality criterion in the MPC controller is formulated as a quadratic functional, minimized taking into account the predictive MIMO model of the distillation column, which ensures coordinated regulation of multi-connected output variables, minimization of deviations in the concentrations of key components from the specified setpoints and limitation of the intensity of control actions while observing technological and operational limitations.

Horizons of prediction and control

The prediction horizon Np and the control horizon Nu are key parameters for tuning the MPC controller and determine the trade-off between the quality of control, stability, and computational complexity of the algorithm when controlling a distillation column.

Np prediction horizon is chosen to be large enough to encompass the dominant dynamic processes, transport delays, and multi-channel interactions characteristic of a distillation column. This allows the MPC controller to proactively account for the impact of disturbances and constraints on the future dynamics of concentrations and temperature parameters.

The control horizon Nu is typically chosen to be less than or equal to the prediction horizon ($Nu \leq Np$) and determines the number of control actions to be optimized at each control step. Beyond the control horizon, control actions are assumed to be constant, which significantly reduces computational costs and enables real-time implementation of the algorithm for a large, multi-connected object.

A rational choice of prediction and control horizons ensures consistent multi-channel system behavior, smooth control actions, and effective compliance with process limitations while maintaining the required quality of control of the rectification process.

The constraint system is an integral part of the MPC controller and ensures compliance with process, operational, and safety requirements when controlling the distillation column. Within the predictive control framework, constraints are explicitly formulated and taken into account directly during the optimization process.

In the control problem under consideration, restrictions are introduced on the control actions, their increments and output technological parameters:

$$u_{min} \le u(k+i) \le u_{max},$$
$$\Delta u_{min} \le \Delta u(k+i) \le \Delta u_{max},$$
$$y_{min} \le y(k+i) \le y_{max},$$

where the boundaries are determined by technological regulations and the physical capabilities of the actuators.

Limits on control actions reflect the permissible ranges of reflux flow rates, boiler heat load, and column pressure, while limits on output variables ensure the maintenance of a specified separation quality, prevention of still overflow, and adherence to temperature conditions on control plates.

Explicit consideration of the system of constraints in MPC allows one to avoid saturation of the executive bodies, increase the stability of the distillation column operation, and ensure optimal behavior of the control system under conditions of strong multi-connectivity and the action of disturbances.

A typical MPC objective function is:

$$j = \sum_{k=1}^{Np} \left| \begin{matrix} e_{k+i} \\ \vdots \end{matrix} \right|_Q^2 + \sum_{k=0}^{Nu} \left| \begin{matrix} u_{k+i} \\ \vdots \end{matrix} \right|_R^2$$

where Np is the prediction horizon, Nu is the control horizon, Q and R are weight matrices.

5. Application of MPC to control of a distillation column

Using an MPC controller with a MIMO model allows for simultaneous control of multiple output parameters, taking into account their mutual influence. This is especially important for distillation columns, where changing one control channel affects several outputs at once.

Within the MPC framework, it is possible to explicitly specify technological constraints, such as:

Permissible temperature and concentration ranges are determined based on process regulations and separation quality requirements and are formulated as constraints on the predicted output variables of the distillation column. Limits on the concentrations of key components in the distillate and bottoms ensure the maintenance of the specified product purity, while temperature limits on the control trays and in the column bottom prevent deterioration of mass transfer and disruption of the thermal regime.

Mathematically, these requirements are described by the following inequalities:

$$T_{min} \le T(k+i) \le T_{max},\ x_{min} \le x(k+i) \le x_{max},$$

where the limits are determined by the physical and chemical properties of the system and the operating limitations of the equipment.

Including temperature and concentration constraints directly into the MPC optimization problem allows for the prediction of possible process failures and ensures stable and safe operation of the distillation column under conditions of multi-connected dynamics.

Limits on flow rates and rates of change of control actions are introduced to account for the physical capabilities of the actuators, prevent saturation, and ensure smooth and stable control of the distillation column. These actions include reflux flow rate, boiler heat load, and feedstock flow rate.

In the MPC formulation, these constraints are specified in the form of constraints on the absolute values of control signals and their increments:

$$u_{min} \le u(k+i) \le u_{max},$$

$$\Delta u_{min} \le \Delta u(k+i) \le \Delta u_{max}$$

Flow rate limits reflect the technologically permissible operating ranges of the equipment, while limits on the rate of change of control actions ensure a reduction in dynamic loads, prevent oscillatory modes, and contribute to increased process energy efficiency .

Explicit consideration of these constraints in the MPC optimization problem allows for the correct interaction between the multi-connected dynamics of the distillation column and the actuators, maintaining control stability under the influence of disturbances.

Liquid level and pressure restrictions are introduced to ensure safe and stable operation of the distillation column, as well as to prevent emergency conditions such as tray flooding, mass transfer failure , and equipment leakage.

Limitations on the liquid level in the cube and/or in characteristic sections of the column are formulated in the form of inequalities:

$$h_{min} \le h(k+i) \le h_{max}$$

and pressure restrictions are in the form of:

$$p_{min} \le p(k+i) \le p_{max}$$

where the limit values are determined by the design characteristics of the column and industrial safety requirements.

Incorporating level and pressure constraints directly into the MPC optimization problem allows for the prediction of potential violations of acceptable operating conditions and proactive adjustment of control actions. This ensures reliable operation of the distillation column under external disturbances and significant process parameter complexity .

The simulation results show that MPC control provides faster disturbance suppression and less overshoot compared to classical control methods.

6. Discussion of results

Using MPC with a MIMO model improves the stability of the distillation column and enhances separation quality. An additional benefit is the ability to optimize energy costs through the rational distribution of control actions.

It should be noted that the efficiency of MPC largely depends on the accuracy of the model and the choice of controller parameters, such as control horizons and weighting coefficients.

7. Conclusion

This article demonstrates the feasibility of using an MPC controller with a MIMO model to control a distillation column. This approach improves the dynamic performance of the control system, enhances product quality, and reduces energy costs . The results obtained can be used in the development of advanced control systems for industrial distillation units.

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