Rectification process control by separation process efficiency evaluation using a predictive model

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Abstract. The article considers the possibilities of optimizing the distribution of components over the height of the rectification column, which is a key factor for achieving high separation efficiency and quality of the obtained products. The efficiency of the rectification process was evaluated according to several criteria affecting product clarity, product compliance with standards, productivity, energy efficiency, and economic efficiency. A dynamic model was used to control the rectification process, the main point of which is to take into account the dynamic changes in the system, which allows a more accurate reflection of the real processes occurring in the rectification column. For the improved process control the predictive model was developed, which allows to identify regularities of the system development, to predict possible scenarios in the state of the control object and to make reasonable management decisions based on future forecasts of the system states.

1 Introduction

The distribution pattern of the separated components over the height of the rectification column depends on several important factors, which together determine the process of separation of the mixture into lighter and heavier components [1,2]. The main factors affecting this distribution are:

- Physicochemical properties of the components (boiling point of the components, relative volatility, component interactions).
- Process parameters (column temperature and pressure, feed, distillate extraction and cube residue extraction rates, column height, column diameter, plate type and design).
- Control parameters (feed parameters, reflux flow rates, reflux-to-product ratios, column temperature points).

Targeted control of these factors allows the distribution of components to be optimized, which ultimately affects the efficiency of the rectification process and the quality of the resulting products [3,4].

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In the process control of rectification separation of mixtures, the values of purposely selected process parameters are maintained within a specified range. Optimal distribution of components in the rectification column is a key factor for achieving high separation efficiency. It is important to take into account all of the above factors that determine the dynamic mode of operation of the rectification column [5]. Changes in the process mode of the rectification process can lead to various results, including:

1. Changes in the quality and quantity of the resulting products:
   - Increase in product purity: changes in the mode may affect the separation efficiency of the components, resulting in higher or lower purity of the resulting products.
   - Changes in product output: changes in the mode may affect the quantity of product output, increasing or decreasing the production volume.
2. Energy conservation and efficiency:
   - Optimization of energy consumption: changes in mode can help to optimize the energy consumption of the rectification process.
   - Improving efficiency: changes in process mode can help improve overall process efficiency, reducing losses and increasing the yield of quality products.
3. Reducing costs and increasing productivity:
   - Cost optimization: the right regime changes can help to reduce the cost of the rectification process.
   - Increase productivity: a new process regime can help increase productivity and process speed.
4. Process stability:
   - Process stability: regular changes in process mode can affect the stability of process operation and predictability of results.

To summarize, it can be concluded that changes in the distillation process regime can have a significant impact on various aspects of the process, including product quality, process efficiency, costs, productivity, safety and stability. The main values to be stabilized in distillation columns are the distillate and cube residue compositions [6,7].

2 Methods and materials

Many criteria can be used to evaluate the efficiency of a distillation process, but the most important criterion depends on the specific objectives and conditions. The choice of criteria may be influenced by product purity, product compliance, productivity, energy efficiency, cost-effectiveness, etc.

Ideally, it is desirable to consider all of these criteria together to achieve optimum efficiency of the rectification process. Often the square of the deviation of the measured temperature profile from the theoretically calculated temperature profile is used to evaluate the efficiency of the rectification process (1) [8].

$$\psi(j, i \cdot T_S) = \sum_{j=1}^{N} \left(T_ч(j, i \cdot T_S) - T_э(j, i \cdot T_S)\right)^2 \rightarrow \min, \tag{1}$$

here j - number of temperatures measuring device, $i \cdot T_S$ - discrete analogue of real time, N - number of temperatures measuring devices.

Optimization of the temperature profile of a rectification column (Figure 1) is aimed at improving separation, reducing energy consumption and increasing productivity. Optimization is possible by: changing the number of column plates, changing the column diameter, changing the column pressure, changing the vapor/liquid flow rate, changing the feedstock composition, using efficient heat exchangers and controlling the operating modes.

Stabilization of pressure and temperature at the ends of the rectification column can ensure a given degree of purity of the separation products.

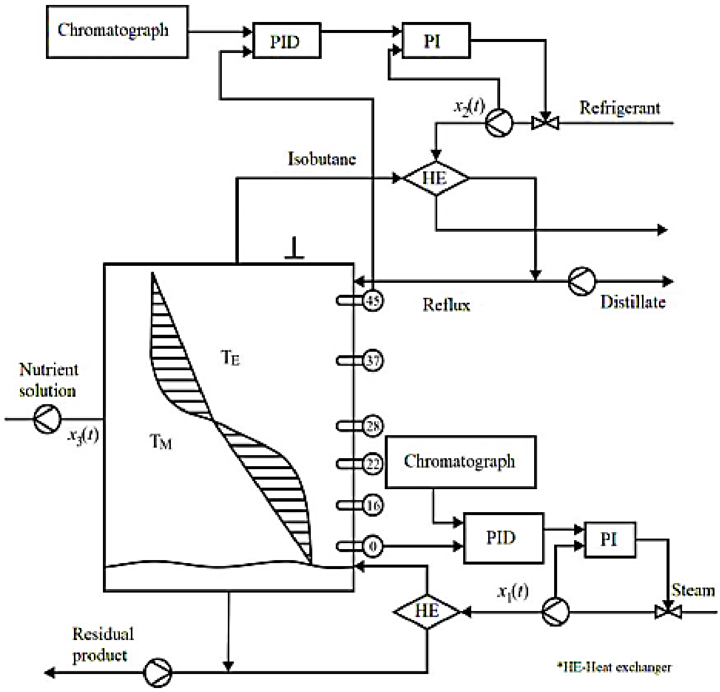

Fig. 1. Graphical representation of distillation column efficiency.

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The control of rectification columns is complicated by the pronounced non-linearity in behavior and operation over a wide range of changes in feed stream compositions. In such cases, a control scheme based on operational forecasting [9] or invariance principles is quite acceptable. The latter provides for corrective control aimed at compensating unaccounted perturbations, for example, deviations of feed flow rate or its temperature by introducing a control loop in the feed fluid heating scheme. The remaining disturbances are determined through indirect measurements. The measurement results are identified as input disturbances. However, even this scheme is not ideal, since in the separation of complex mixtures with near-boiling volatile components, even significant changes in inlet disturbances cannot lead to any appreciable temperature changes at the top of the column. Consequently, temperature control cannot provide the required distillate quality. In a dynamic model of the rectification process, the defining point is the consideration of temporal changes in the state variables of the system in time. Such a model takes into account not only equilibrium conditions and stationary processes, but also the dynamics of parameter changes during the transition from one equilibrium state to another.

In the development of a dynamic model of the rectification process, the main point is to take into account the dynamic changes in the system, which allows a more accurate reflection of the real processes occurring in the rectification column [10,11].

The requirements for the content of volatile components at the ends of the column, the flow rate F and the chemical component F_x. must be specified to make a dynamic model of the process. Calculations are carried out using the material and heat balance equations.
The equilibrium concentration in the vapor phase is determined by the equation:

$$Y^*_{k,j} = \frac{\gamma_{k,j} p^0_{k,j}}{p_j} x_{k,j} = K_{k,j} x_{k,j}. \tag{2}$$

In order to simplify the calculations, the partial vapor pressures of individual components p^0_kcan be calculated using the Antoine equation:

$$log[p^0_k] = A - \frac{B}{T+C}. \tag{3}$$

The composition of steam passing to the next plate can be determined by equation (4), and the efficiency of the plate in terms of Murfree's coefficient of efficiency can be calculated by equation (5).

$$y_{jk} = \left(1 - \eta_{Ty_{jk}}\right) y_{j-1,k} + \eta_{Ty_{jk}} y^*_{jk}, \tag{4}$$

$$\eta = \frac{y_{k,j} - y_{k,j-1}}{y^*_{k,j} - y_{k,j-1}}, \tag{5}$$

The balance for each component k, of the power composition, on each j - plate is $(k = 1, \dots, n_k;\ j = 1, \dots, n_t)$ determined by equation (6):

$$\frac{dn_{k,j}}{dt} = \frac{d(n_j x_{k,j})}{dt} = F_j x_{F,k,j} + L_{k,j-1} - (L_j + S_{1,j}) x_{k,j} + (V_{j+1} - S_{V,j+1}) y_{k,j+1} - V_j y_{k,j}. \tag{6}$$

The balance for each component k in the capacitor $(k = 1, \dots, n_c)$ can be calculated using equation (7):

$$\frac{dn_{k,0}}{dt} = \frac{d(n_0 x_{k,0})}{dt} = (V_1 - S_{V,1}) y_{k,1} - (L_0 + D) x_{k,0}. \tag{7}$$

Among the assumptions adopted, the liquid phase in the column cube is assumed to be perfectly mixed:

$$\frac{dn_{k,j+1}}{dt} = \frac{d(n_{j+1} x_{k,j+1})}{dt} = L_j x_{k,j} - W x_{k,j+1} - V_{j+1} y_{k,j+1}. \tag{8}$$

The total liquid content of each plate j can be calculated from the sum of the quantities of the individual components:

$$n_j = \sum_{k=1}^{n_k} n_{k,j}. \tag{9}$$

The upward steam fluxes are calculated from the energy balance. For each individual plate, this balance is written as equation (10):

$$n_j \frac{dh'_j}{dt} = [F_j (h'_{F,j} - h'_j) + L_{j-1}(h'_{j-1} - h'_j) + (V_{j+1} - S_{v,j+1})(h''_{j+1} - h'_j) - V_j (h''_j - h'_j)]. \tag{10}$$

V_j of steam flow rate is determined by the equation:

$$n_j = \frac{1}{h''_j - h'_j} [F_j (h'_{F,j} - h'_j) + L_{j-1}(h'_{j-1} - h'_j) + (V_{j+1} - S_{v,j+1})(h''_{j+1} - h'_j) + (V_j - S_{v,j} + 1)(h''_{j+1} - h'_j)]. \tag{11}$$

3 Results and discussion

The solution of the mathematical description allows to obtain the profile of concentrations and temperature along the column height, and by calculating their gradients it is possible to determine the position of the control plates. Figure 2 shows the profile of temperature along the height of the rectification column, the analysis of which shows the location of the control plates, and Figure 3. shows the profiles of concentrations of components calculated at different values of product flows and feed compositions.

The plate-by-table model of the distillation column allows to specify the location of the control plates determined taking into account other factors as well.

Based on the comparison of the two temperature profiles (Figure 2 and Figure 3), it can be assumed that there is a different effect of the two control schemes on the temperature profile. The true difference is that a variation of ΔD = ± 1.00 (Figure 3) has a greater effect on separation capacity than a variation of ΔL = ± 1.00 (Figure 2).

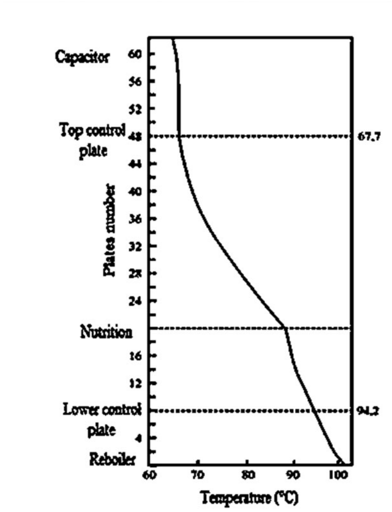

Fig. 2. Temperature profile of the rectification column.

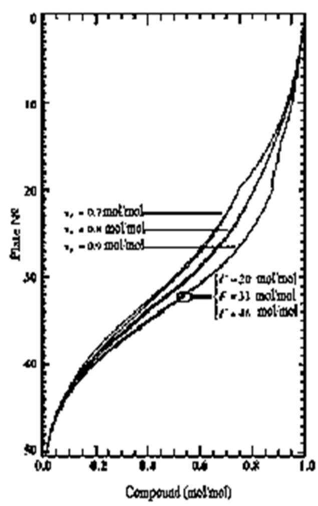

Fig. 3. Concentration profile of the rectification column.

The effect of varying the irrigation flow rate and distillate extraction rate on the temperature profile at stable cube steam supply is shown in Figures 4 and 5.

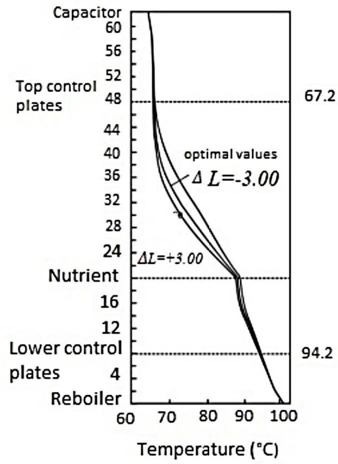

Fig. 4. Effect of changing the irrigation flow rate on the temperature profile at stable steam supply to the cube.

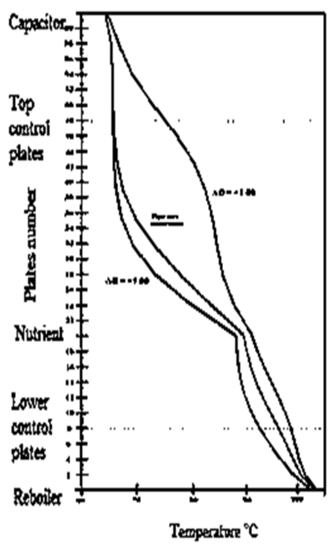

Fig. 5. Effect of distillate withdrawal value on temperature profile at stable steam supply to the cube.

Analyses of temperature profiles calculated at different values of determining factors have shown their indispensability in separation quality control, when there is no possibility of direct measurement of compositions.

To control the technological process, it is necessary to purposefully select and support certain variables within a given range of their variation, since such parameters as the amount and composition of raw materials, the values of withdrawn product flows and irrigation, etc. change within a certain range. The said variables can be utilized in a control system using feedback. For example, when controlling product concentration, the measurements allow the control system to adjust the process parameters to achieve the desired concentration. These variables may be used in optimal control using prediction of numerical values of these parameters to control the process according to a predetermined law or controller. In addition, these variables can be used in model-predictive control: measurements can also serve to correct model predictions of the process, thereby improving the accuracy and efficiency of control.

So, the measured values of concentrations or temperatures play an important role in the functioning of the control system, providing better accuracy, efficiency and reliability of the process.

The process is controlled by varying the phlegm and vapor flow rates. If we assume that on a single time section the values $L = const$ and $V = const$, while the liquid on the plates is described by the model of ideal mixing, the solution of the material balance equation can be obtained by a piecewise linear approximation of equation (12):

$$x = x_H e^{-\frac{a}{H}t} + \frac{b}{a}\left(1 - e^{-\frac{a}{H}t}\right).$$
$$t \in T = t_{j+1} - t_j \tag{12}$$

There:

$$ta = L(1 - \frac{1}{1-\eta} + \frac{\eta R}{m(1-\eta)(R+1)}) + K_{xv}(1 - \frac{R}{m(R+1)}).$$
$$b = \frac{K_{xv}x_d}{m(R+1)} - \frac{L\eta x_d}{m(1-\eta)(R+1)} \tag{13}$$

Phlegm flow control is generally based on achieving and maintaining the desired phlegm/product ratio, which provides optimum conditions for efficient operation of the distillation column.

The basic conditions for phlegm flow control are:

1. Degree of separation: the phlegm flow rate can be controlled to achieve a certain level of separation of the components in the column. Increasing or decreasing the phlegm flow rate can affect the amount of circulating liquid and therefore the separation efficiency.
2. thermal balance: maintaining an optimum phlegm flow rate is important to maintain thermal balance in the column, which affects the uniform vaporization and condensation of the components.
3. Concentration control: controlling the phlegm flow rate allows controlling the concentration of the components in the column, which is important for obtaining the desired products.
4. Minimization of the time of deviation of the measured current concentration value from its set point determined by formula (14):

$$R_1 = \min_{L_0 > L > L_{xt}} \left| x_3 - x(t) \right|. \tag{14}$$

The principles of phlegm flow control are:

- Feedback: a feedback control system is often used where measurements of parameters such as concentrations or temperature help to adjust the phlegm flow rate to maintain optimum process conditions.
- Predictive control: simulates process dynamics and helps to predict changes in the system, allowing the phlegm flow rate to be optimized in advance to achieve specified goals.

Phlegm flow control is important to ensure efficiency, stability and optimum separation of components in a distillation column, and this is achieved by controlling the ratio between phlegm and product.

A measure of how well the control system controls the temperature at the top of the column is the Upper Temperature Profile Control Quality Criterion (TPCQC). Aspects included in this quality criterion are: temperature stability, control of overheating or under heating, minimization of temperature changes in response to perturbations, a good control quality criterion includes the ability to minimize temperature changes in response to perturbations, consideration of system operation, and compliance with desired product quality parameters. In addition, the CCUWPT is a measure of the current losses of raw materials. These losses can be calculated from the difference between the measured amount of feedstock $f_u(j \cdot T_s)$, entering with feed, and leaving with distillate, determined by the predictive model $f_n(j \cdot T_s)$.

$$\begin{cases} \Delta J_v(J \cdot T_s) = f_u(j \cdot T_s) - K_{dr} \cdot f_n(j \cdot T_s), \\ \Delta J_v(j \cdot T_s) \geq 0, f_n(j \cdot T_s) \geq 0, f_u(j \cdot T_s) \geq 0 \end{cases} \tag{15}$$

In this expression $\Delta J_v(j \cdot T_s)$ - shows the amount of lost component when stabilizing the phlegm flow rate, T_s - time of each measurement cycle, $f_n(j \cdot T_s) = M\{X_3(k \cdot T_s)\}Z_7(j \cdot T_s)$ - predicted losses of component in distillate, $X_3(k \cdot T_s)$ - measured distillate flow rate, T_s - polling time of sensors, $M\{X_5(k \cdot T_s)\}$ - mathematical expectation of distillate flow rate, $Z_7(j \cdot T_s) = M\{Z_7(k \cdot T_s)\}$ predicted concentration value of the component, K_{dr} - tuning factor, $f_u(j \cdot T_s) = M\{X_4(k \cdot T_s)\}Z_3(j \cdot T_s)$ - component loss in the power line, $X_4(k \cdot T_s)$ - power flow, $Z_3(k \cdot T_s)$ - concentration of the component in the power supply.

In the predictive model equation (16), the parameter reflecting the concentration of components in the column feed is – $\Delta J_v(j \cdot T_s)$, is not stable, but 'drifts' in the parameter field. On this basis, a control criterion is often used to evaluate the efficiency of the rectification column operation, ensuring the minimum feedstock losses, using adaptive control (16):

$$\begin{cases} J_v(N_m \cdot T_s) \Rightarrow \min\limits_{K_{dr}} \sum\limits_{j=0}^{N_m} f_u(j \cdot T_s) - K_{dr}(j \cdot T_s) \cdot f_n(j \cdot T_s), \\ J_v(N_m \cdot T_s) \geq 0, f_n(j \cdot T_s) \geq 0, f_u(j \cdot T_s) \geq 0 \end{cases} \tag{16}$$

In this term $J_v(N_m \cdot T_s)$ - are the sum of all losses at phlegm number control at the time interval $N_m \cdot T_s$. T_s – shows the duration of the concentration measurement time, N_m – shows the sample size estimating the losses on the control time interval $T_y = N_m \cdot T_s$, $K_{dr}(j \cdot T_s)$ - coefficient that takes into account drifting properties of the criterion.

The results of calculations on optimal control of concentration, temperature at the control system plate in the strengthening part of the column and phlegm flow rate are presented in Figures 6-8.

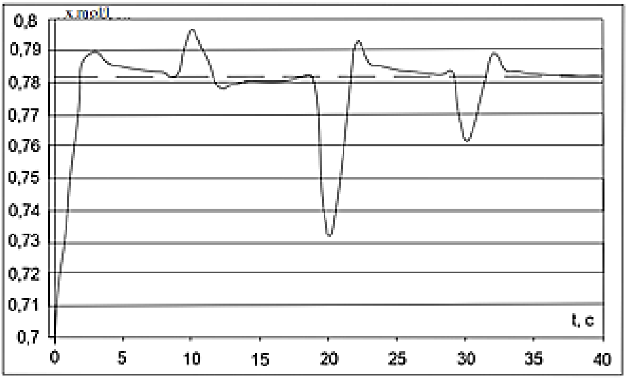

Fig. 6. Transient characteristic of concentration change.

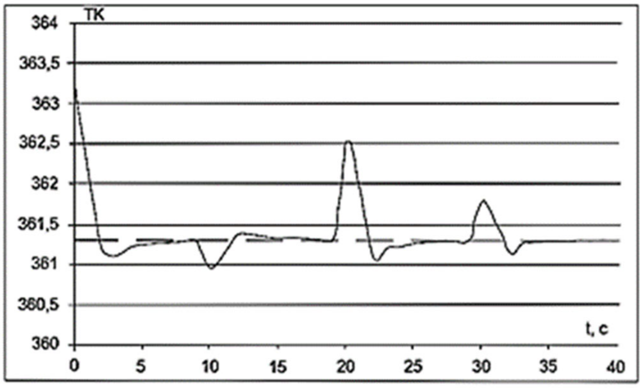

Fig. 7. Transient characteristic of temperature change.

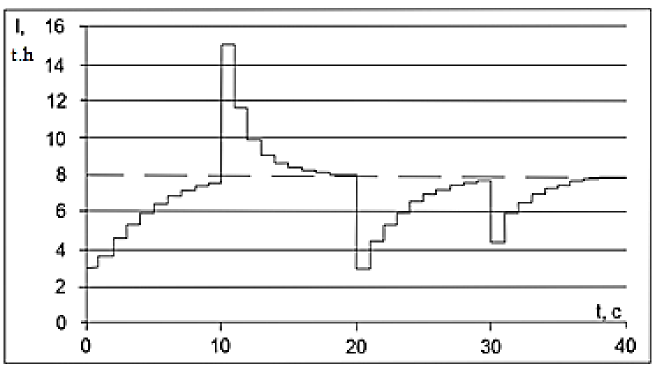

Fig. 8. Transient characteristic of phlegm flow rate variation.

The developed method, allowing to determine the optimal phlegm number, is realized in the form of the CCUWPT with anticipation. This allows to improve the quality of control of the upper part of the rectification column (Figure 9).

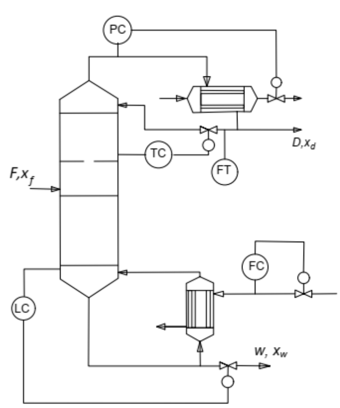

Fig. 9. Principal scheme of quality control of column distillate.

In order to improve the quality of rectification process control, an MPC approach using the 'MIMO-model' has been developed.

The essence of MPC approach to control is defined in the sequential performance of the following operations:

- using a predictive process model to optimize control actions in real time, taking into account process dynamics, production targets and constraints;
- selection of a relatively simple model of the rectification column with initial conditions in the form of the state of the object at a given moment of time;
- determination of the 'forecast horizon' (the period of time for which the forecast or planning is made).

Optimization of program control using the MPC approach is carried out in order to: predict future process variation and take preventive measures, minimizing cycle time and maximizing throughput; improve process performance; adapt control to changing process conditions, taking into account external factors (temperature, pressure, feedstock composition) and internal constraints and improve control quality.

Next, a transition is made to the iterative computations used in control algorithms to find the optimal control strategy in real time, involving the calculation of controllers, prediction of actions, correction of control actions and decision making based on current data and predictions.

Past data and expert knowledge are used to create a mathematical model of the process that describes its dynamics and the relationships between input and output parameters (Equations 17, 18). Based on the process model and current data, a prediction of future values of the controlled parameters is made.

When using the MPC approach to control, a simple linear model of the form:

$$\dot{x}(t) = f(t, x(t), u(t)), \tag{17}$$

$$x(0) = x0, \tag{18}$$

where $x \in E^n$, $u \in E^m$ – control vectors, and $t \in [0, \infty)$ – condition vector.

Linear models are much easier to understand, develop and implement in software. optimization algorithms for linear models are also much more efficient and faster than for non-linear models. These models have sufficient accuracy for many processes (for many industrial processes, linear models provide a reasonably accurate description of the system's behavior over a narrow range of operating points, which allows MPC to be used for effective process control without overloading the system with complex nonlinear models). In addition, parameter identification of linear models is generally simpler and requires less data than parameter identification of nonlinear models [12,13].

Thus, choosing a linear model as an initial step in MPC provides a balance between simplicity and accuracy and allows the construction of efficient control for many processes.

Assuming that there exists a set of controls $U \in Em$ and states $X \subseteq En$, then for any admissible moment $t \in [0, \infty)$, the conditions $x(t) \in X$, $u(t) \in U$ must be satisfied.

Suppose the sets U and X are defined by relations (19) and (20).

$$U = \left\{ u \in E^m : u_{i\min} \le u_i \le u_{i\max}, i = \overline{1, m} \right\} \tag{19}$$

$$X = \left\{ x \in E^n : x_{j\min} \le x_j \le x_{j\max}, j = \overline{1, n} \right\} \tag{20}$$

In relations (19) and (20) – $u_{i\ min}$, $u_{i\ max}$, $x_{j\ min}$, $x_{j\ max}$ – specified real numbers.

Next, the control actions (e.g. temperature change, raw material flow rate) that need to be applied to achieve optimal process control are selected, the control is implemented and the actual behavior of the process is monitored. If the deviation from the optimal behavior exceeds acceptable limits, the MPC algorithm recalculates the control taking into account the results obtained. Further, the whole process (data collection, modelling, optimization, implementation) is repeated regularly (with a small time step), which allows the control to adapt to changes in the process and external conditions.

Suppose that the goal of control based on the system of equations (21, 22) is to ensure the equality:

$$\lim_{t\to\infty} \|(t) - rx(t)\| = 0, \tag{21}$$

$$\lim_{t\to\infty} \|(t) - r_u(t)\| = 0. \tag{22}$$

In these expressions, $rx(t)$ and $rU(t)$ are vector functions that must be specified. They are intended to determine the required motion of the object. If the control quality functional is represented in the form:

$$J_0 = J_0(x(t), u(t)) \tag{23}$$

we will search for the optimal control action (from among the admissible control sets U) leading to the control objective, expressed in the form (22, 23) taking into account the constraints $x(t) \in X \forall\ t \in [0, \infty)$, and the functional (24) must reach its minimum.

There are a certain number of methods for solving optimal control problems.

The main challenge of implementing optimal control is the high complexity of composing an accurate mathematical description.

Consider the following system of equations:

$$\bar{x}(\tau) = f(\bar{\tau}, \bar{x}(\tau), \bar{u}(\tau)), \tag{24}$$

$$\bar{x}(\tau) = t(0) = x(t), \tag{25}$$

The last system of equations represents the predictive model.

The introduction of the predictive model is due to several fundamental reasons that make it appropriate in various fields, which include:

1. Anticipating future states: a predictive model allows anticipation of future states of a system based on current data. Based on the process model and current data, a prediction of future values of the controlled parameters is made (Figure 10).
2. Informed decision making: with a predictive model, informed decisions can be made based on future state predictions.
3. Optimization of control and resources: predictive models allow optimizing the use of resources and controlling the system based on predicted behavior.
4. Preventing accidents and disturbances: predictive models allow preventing potential accidents, failures and disturbances, so that measures can be taken to avoid potential problems.

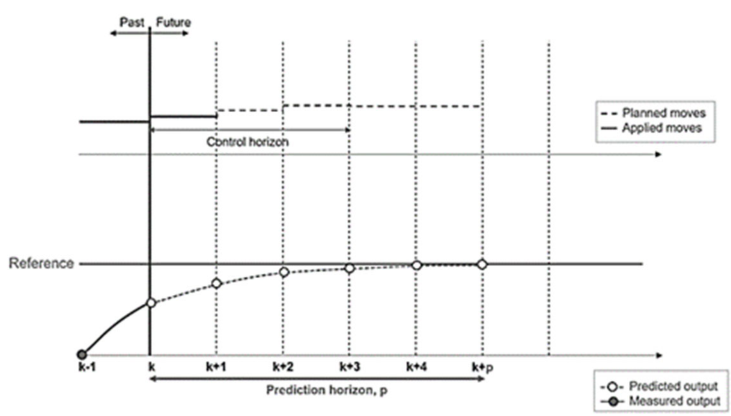

Fig. 10. Scheme for making a prognosis.

Thus, the introduction of a prognostic model is justified because it allows us to identify regularities of the system development, predict possible scenarios, and make informed managerial decisions based on future forecasts of the system states.

It is possible to predict the behavior of the system, but only on the basis of a partial solution of the system (25, 26), provided that the control on the time interval $\tau \in [t, t+T]$ is given. The result obtained depends on the value of T (T> 0), the smaller it is, the more accurate the result is.

Suppose the control $\bar{u} = \bar{u}(\tau)$ is represented as a function on the time segment $\tau \in [t, t + Tp]$. It is required to integrate the system (25, 26) under the initial conditions $\bar{x}|\tau{=}t = x(t)$. The integration of the system (25, 26) results in the partial solution y = $\bar{x}(\tau, x(\tau, x(t), \bar{u}(\tau))$, which is the predicted behavior of the control object with prediction horizon T_p.

The further behavior of the predictive model depends on the functions $rx(t)$ and $rU(t)$, $rx(t) \in En$, $rU(t) \in Em$. To evaluate the quality of control with the predictive model, a functional of the following form is used:

$$j(x(t), \overline{u}(\cdot), T_p, T_s) = \int_t^{t=Tp} F(\bar{x}(\tau, x(t), \overline{u}(\tau)), \overline{u}(\tau), r_x(\tau))d\tau \quad , \tag{26}$$

where T_s – “control horizon”, its value may be equal to or less than T_p.

“Control horizon” represents a specific point in time, such that:

$$\overline{u}(\tau) = \overline{u}(t + T_S)\forall \tau \in \left[t + T_S; t + T_p\right] \tag{27}$$

In scientific research, it is quite common to use a sum consisting of two quadratic forms (28) to reflect the sub-integral function of a functional:

$$F = (\bar{x} - rx)' R(\bar{x} - rx) + (\bar{u} - ru)' Q(\bar{u} - ru) \tag{28}$$

In this expression R and Q are matrices satisfying two important properties: they are symmetric and positively definite.

A symmetric matrix is a matrix that is equal to its transposed form. That is, the elements of the matrix are the same with respect to the main diagonal. Formally, if we have a matrix A, then A is equal to its transposed form A^T.

A matrix is said to be positively definite if the condition x^T * Ax > 0 is satisfied for any non-zero vector x, where ^T denotes the transpose operation. This means that the determinant of all principal minors of the matrix is positive.

The problem posed to the optimal control in order to be used in a predictive model can be represented in the form (29)

$$j(x(t), \overline{u}(\cdot), T_p, T_S) \to \min_{\overline{u}(\cdot) \in \Omega_u} \tag{29}$$

where:

$$\Omega_u = \left\{\overline{u}(\cdot) \in k_n^0\left[t, t + T_p\right] : \overline{u}(\tau) \in U, \overline{x}(\tau, x(t)) \in X, \forall \tau \in \left[t, t + T_p\right]\right\} \tag{30}$$

The last relation (30), represents one of the admissible sets of controls, where $K_n^0\left[t, t + T_p\right]$- is a set of piecewise continuous functions defined on the time interval $[t, t + Tp]$.

The solution of equation (29) appears as a vector (30):

$$\overline{u} * (\tau) = \overline{u} * (\tau, x(t), T_p, T_s) = \arg\min j(x(t), \overline{u}(\cdot), T_p T_s) \overline{u}(\cdot) \in \Omega_u \tag{31}$$

It should be noted that it is not always possible to achieve a perfect match between the real process behavior and the model prediction, especially in the case of unknown disturbances and noise. In this case, it is necessary to:

- check the accuracy of the process model used in the MPC;
- analyze the influence of measurement noise and unknown disturbances on the process, considering the possibility of improving the filtering of the data;
- verify that the MPC parameters are correctly set;
- to clarify the constraints set for the process control and to exclude errors in the MPC algorithm calculations.
- if inaccuracy of the model is detected - update it using new data;
- if an inaccuracy in the MPC parameter settings is detected, adjust these parameters to minimize the difference between the actual process behavior and the model prediction.

By following these guidelines, it is possible to improve the quality of control and minimize the deviation from optimal control when using the MPC approach.
The adjusted control in this case is represented by the identity (32)

$$\bar{u}*(\tau) \equiv \bar{u}*(\tau, x(t), T_p, T_S), \tau \in [t, t+\delta] \quad (32)$$

where the value of the coefficient δ exceeds 0 but is much smaller than Tp.

The calculation of the next predictive behavior of the control object with a prediction horizon Tp in the MPC approach is carried out as follows:

A process model describing its dynamics and the dependencies between input and output variables is used. The model can be linear or non-linear, depending on the complexity of the process.
Let us consider an example of using a linear model.

$$x(k+1) = Ax(k) + Bu(k) + w(k)$$
$$y(k) = C*x(k) + v(k)$$

where:
x(k) - state of the system at time k
u(k) - control action at the moment of time k
y(k) - output data of the system at the moment of time k
A, B, C - matrices of model parameters
w(k) - process noise
v(k) - measurement noise

The prediction horizon (Tp) determines the number of future time steps for which a prediction is made. The choice of prediction horizon depends on the dynamics of the process and the requirements for prediction accuracy. A horizon that is too small may not account for future changes in the process, and a horizon that is too large may cause the prediction to lose relevance due to system instability. Next, using the process model and the current values of state and control action, the predicted values of system state and output at each time step within the prediction horizon are calculated. The calculation of the prediction may use previous data on the process behavior, and process and measurement noise must be taken into account. The calculation results in a set of predicted values of the state and output of the system at each time step within the prediction horizon. The prediction can be presented in the form of a graph, table or other visual aids for ease of analysis and interpretation.

Thus, the calculation of the next predictive behavior of a control object with a prediction horizon Tp in the MPC approach is based on using a process model and recursively applying it to calculate the predicted values at each time step within the prediction horizon.

4 Conclusion

A predictive control system based on predicting the behavior of the system and making control decisions based on these predictions has been developed on the basis of this research. It is shown that the choice of a linear model as an initial step in MPC provides a balance between simplicity and accuracy of the model and allows the construction of effective control for many processes.

The predictive model, using the target function defining the desired criterion for assessing the quality of control, allows to identify regularities of the system development, predict possible scenarios and make informed management decisions based on future forecasts of the system states.

References

1. D.P. Mukhitdinov, Y.B. Kadirov, I.R. Sultanov, Journal of Physics: Conference Series **2373(7)**, 072025 (2022).
2. Müller Magdalena, Thomas Becker, and Martina Gastl, Foods **10(7)**, 1602 (2021).
3. H. Li, H. Liu, Y. Li, J. Nan, C. Shi, & S. Li, Energies **14(8)**, 2266 (2021).
4. T.G. Korotkova, G.I. Kas'yanov, Russian Journal of Physical Chemistry **95**, 1051-1060 (2021).
5. J. Zhang, J. Xu, Y. Wang, X. Gao, Chem. Eng. Res. Des. **145,** 268-280 (2019).
6. K. Wen, H. Xu, M. Xu, Y. Pei, Y. Lu, H. Zheng, Zh. Li, Measurement **217,** 113140 (2023)
7. K.Y. Thajudeen, M.M. Ahmed, S.A. Alshehri, Sci Rep **14,** 23970 (2024).
8. Y.-W. Je, Y.-J. Kim, Y.-J. Kim, Processes **10,** 375 (2022).
9. A. Sheikus, V. Kovalenko, V. Kotok, I. Levchuk, O. Bilobrova, L. Darovskih, EUREKA: Physics and Engineering **6,** 33-40 (2020).
10. E A Muravyova, IOP Conf. Ser.: Mater. Sci. Eng. **976**, 012007 (2020).

    M.J. Claus, K.A. Berglund, Journal of Food Process Engineering **28(1)**, 53-67 (2005).