# MATHEMATICAL MODELING OF OPERATIONAL-DISPATCHING PROCESSES OF COMPLEX TECHNOLOGICAL OBJECTS

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***Abstract.*** *Mathematical modeling of the processes of operational dispatch control of complex technological objects was carried out using the example of catalytic cracking of oil. It is shown that further progress in the catalytic cracking of hydrocarbon feedstock is associated with the involvement of heavy vacuum distillates, fuel oils and other oil residues as feedstock for the production of high-octane gasoline fractions, as well as with the implementation of improved or advanced control systems and development of adaptive algorithms for operational dispatching predictive control that allow control systems to track the current technological situation and form control actions that are adequate to it, compensating for uncontrollable disturbances.*

***Keywords:*** *Catalytic cracking, Operational predictive control, Advanced Process Control, Neuro-fuzzy control systems, Predictive controller, Hybrid model.*

## Introduction

Modern control systems operate under conditions of internal and external random disturbing influences of a parametric, adaptive and multiplicative nature. The problem of decision support in systems of operational and predictive control of complex technological processes and industries can be characterized by an abundant flow of research and development in the field of modern theory of control of complex technological processes and industries, supported by the powerful development of modern information technologies and the powerful development of computer technology.

Currently, one can observe qualitative strategic changes in the principles of making managerial decisions in conditions of information uncertainty and risks accompanying the operational and predictive control of industrial production. At the same time, if the content side of decision-making algorithms in operational and predictive control of technological processes and industries (in particular, sequential correction of technological modes based on the results of operational monitoring, laboratory analyzes, expert assessments) remained unchanged, then their optimization component and focus undergoes significant changes and continues to result in a number of new developments, in particular, united by a common methodology Advance Process Control & Optimization (APC) - an improved (or advanced) control system [1].

One of the promising approaches to structural-parametric analysis and synthesis of control systems for complex technological processes and industries is the control technology using predictable models, which provides the relative simplicity of the basic feedback formation scheme and allows you to control multidimensional and multi-connected objects in real time under risk and uncertainty of external and internal information. In this regard, the complex scientific and technical problem of implementing the methodology of ARS-systems of advanced control for decision-making in the context of operational and predictive control of complex technological processes and industries using the example of industrial installations for the catalytic cracking of oil is undoubtedly relevant and in demand.

Currently, catalytic cracking is the largest and most important of the catalytic oil refining processes. This process was widely developed in the USA and in the countries of Western Europe. The total capacity of catalytic cracking units in the USA reached about 35% of the capacity of primary oil refining, 13.9% - in Western Europe and 6.0% - in Russia. Theoretical foundations, process technology, modern schemes and hardware design of catalytic cracking units are presented in the works of Smirdovich E.A., Bondarenko B.I., Sukhanov V.P., Melnikov V.B., Khairudinov I.R., Glagolev O. F., Ishmiyarova M.Kh. ... The issues of control of catalytic cracking units, mathematical modeling, optimization and operational dispatch control of the processes occurring in the reactor block are considered in the works of Serebryansky A.Ya., Mett A.Yu., the study of the process of regeneration of coked catalyst after cracking and its modeling are considered in Massagutova R.M.

The technological mode of cracking depends on the characteristics of raw materials and catalyst, atmospheric air, etc., not all of which can be measured or measured in laboratory conditions, which leads to the need to use expert experience as part of automation control systems for installations. The technological process is subject to strict restrictions on the range of values of temperature, concentration and pressure in the apparatus of the reactor block. One of the ways to use the experience of the operational dispatching personnel is to use the mathematical apparatus of the theory of fuzzy sets for the algorithmization of control decision-making problems [2].

In recent decades, a number of works have been published (Aliev R.A., Yusupbekov N.R., Azeem MF, Osoffsan PB, Taskin H., Vyalykh I.A., Shumikhin A.G., Abdullaev A.R., Verevkin A. P., Akhmetov S.A., Anisimov I.V., Dokuchaev E.S.) using the methods of the theory of artificial intelligence in the control algorithms of the catalytic cracking reactor block. At the Perm National Research Polytechnic University, Vyalykh I.V. A dissertation work was carried out on the development of algorithms for intellectualization of the technological process control system of the reactor block of a catalytic cracking unit for vacuum gas oil based on fuzzy production models of the presented expert knowledge with automatically generated membership functions for the values of linguistic variables in conditions of incomplete information.

An analysis of the degree of knowledge of the problem indicates the relevance of the problem of developing adaptive algorithms that allow the control system to track the current technological situation and make control decisions, forming control actions that effectively compensate for uncontrollable disturbances. There is a growing demand for further intellectualization of support systems for decisions made in operational-predictive control in order to improve the quality of their functioning and ensure energy and resource conservation.

## 2. Modeling and control of the oil catalytic cracking process

Recently, in order to ensure high economic efficiency of control of complex technological complexes and installations, there is a merger of automated control systems for technological processes (ACSTP) and production (ACSP) into unified integrated information control systems (ICS) of an organizational and technological type (APCS). The most important links of such systems are automated operational dispatch control systems (AODCS), which carry out operational control of complex technological processes and industries, transforming control decisions of the upper control level into technological ones and solving the problems of predicting the course of production processes, and the decision maker (DM), on based on predictive information, it has the ability to effectively implement control actions [3].

Further progress of the catalytic cracking process is associated with the involvement of heavy vacuum distillates of fuel oils and other oil residues as feedstock for the production of high-octane gasoline fractions, as well as with the implementation of ARS-systems of advanced control and the development of adaptive algorithms for predictive control that allow control systems to track the current technological situation and form control actions adequate to it, compensating for uncontrollable disturbances. A two-level system for intelligent control of the catalytic cracking process is proposed, which includes a level of decision-making to maintain an optimal static regime and a level of control over the dynamics of the catalytic cracking process based on a neuro fuzzy genetic based approach. Fuzzy control algorithms and their computer implementation have been brought to a form that allows them to be integrated using the OPC DA (Ole for Process Control Data Access) protocol and to be applied in an operating information control system in supervisory or automatic mode.

Predicting the future performance of a technological object and determining the optimal value of the control action are two computationally complex procedures that the predictive controller has to deal with within the same sampling rate. This is one of the main reasons that this type of regulator is mainly used for slow processes. To overcome this drawback of predictive controllers (predictable logic controllers), it is necessary to develop ways to facilitate the calculation procedure in modeling and optimization of the control object [4].

In this regard, the presented work is aimed at developing algorithms for the functioning of predictive controllers based on neuro-fuzzy models with a reduced number of fuzzy rules and having a small number of tuning parameters. The goal is formulated - the development of a distributed model of neuro-fuzzy forecasting with the Takagi-Sugeno deduction mechanism with an optimized number of fuzzy rules suitable for predictive control purposes.

The first input layer of the model is nonparametric and reflects the distribution of the input signals. The second layer of the predictive model is parametric and performs the blur operation using Gaussian helper functions described by the following relationship:

$$\mu^{(n)}_{Xp,m} = \exp\frac{-(x_p - x_{Xp,m})^2}{2\sigma^2_{Xp,m}} \tag{1}$$

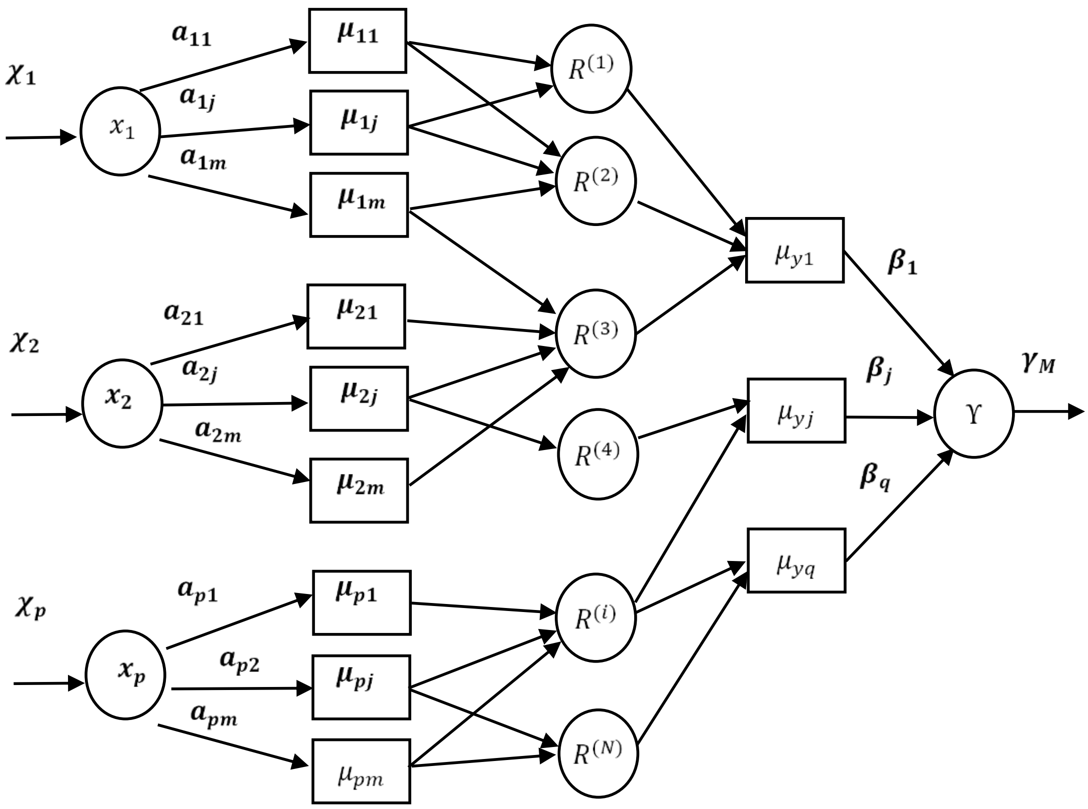


*Fig. 1.* ***Neuro-fuzzy structure of the hybrid model of the research object.***

At the third level, the mathematical model is a kind of rule generator, since its fuzzy logical rules are formed in the following form:

$$\begin{aligned} &R^{(N)}: if\ x_1(k+j) is\ \tilde{X}^{(N)}_1 and\ x_1(k+j) is\ \tilde{X}^{(N)}_2 \ldots \\ &if\ x_p(k+j) is\ \tilde{X}^{(N)}_1 then\ f_y^{(N)}(k+1) \end{aligned} \tag{2}$$

The last two layers of the model are nonparametric and form a diffuse outflow mechanism. At the fourth level, the operation is carried out using the weighted average work:

$$\mu^{(n)}_{yq}(k+j) = \mu^{(n)}_{x_1,m}(k+j) * \mu^{(n)}_{x_2,m}(k+j) * \ldots * \mu^{(n)}_{x_p,m}(k+j) \ . \tag{3}$$

At the fifth level, a decision is made to determine the value of the output quantity using the expression:

$$\hat{y}_M(k+j) = \frac{\sum_{i=1}^{q} f_y^{(i)}(k+j)\mu_y^{(i)}(k+j)}{\sum_{i=1}^{q} \mu_y^{(i)}(k+j)} \tag{4}$$

To determine the control effect in the optimizer, an iterative optimization algorithm is solved from the first line. The standard quadratic generalized predict control target was used, assuming no constraints. The target criterion has been transformed into a matrix:

$$J[k, U(k)] = [R(k) - \hat{Y}(k)^T\big[R(k) - \hat{Y}(k)\big] + \lambda\tilde{U}(k)^T\tilde{U}(k) \tag{5}$$

Minimization of the generalized predict control criterion is based on calculating the gradient vector of the objective function in the $k$ th relative to the predicted values of the control action:

$$\nabla J[k,U(k)] = \left[\frac{\partial J[k,U(k)]}{\partial(\mathrm{k}+1)}, \frac{\partial J[k,U(k)]}{\partial u(\mathrm{k}+1)}, ..., \frac{\partial J[k,U(k)]}{\partial u(\mathrm{k}+N_u-1)}\right]. \tag{6}$$

Depending on the matrix equation, the elements of the gradient vector can be represented as follows:

$$\frac{\partial J[k,U(k)]}{\partial U(\mathrm{k})} = \left[-2[\mathrm{R(k)} - \hat{\mathrm{Y}}(\mathrm{k})]^T \frac{\partial\hat{Y}(k)}{\partial U(\mathrm{k})} + 2\lambda\hat{U}(\mathrm{k})^T \frac{\partial\hat{Y}(k)}{\partial U(\mathrm{k})}\right]. \tag{7}$$

From this expression it follows that it is necessary to calculate two groups of partial derivatives. The first group of derivatives can be written as the following matrix:

$$\frac{\partial\hat{Y}(k)}{\partial U(\mathrm{k})} = \begin{bmatrix} \frac{\partial\hat{y}(k+N_1)}{\partial u(\mathrm{k})} \cdots\cdots \frac{\partial\hat{y}(k+N_1)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \frac{\partial\hat{y}(k+N_2)}{\partial u(\mathrm{k})} \cdots\cdots \frac{\partial\hat{y}(k+N_2)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} \end{bmatrix}_{[(\mathrm{Np}-\mathrm{N1}+1)xNu]}. \tag{8}$$

The second group of derivatives is given by the matrix:

$$\frac{\partial\hat{U}(k)}{\partial U(\mathrm{k})} = \begin{bmatrix} \frac{\partial\Delta u(k)}{\partial u(\mathrm{k})} \cdots\cdots\cdots\cdots \frac{\partial\Delta u(k)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \frac{\partial\Delta u(k+N_u-1)}{\partial u(\mathrm{k})} \cdots\cdots \frac{\partial\Delta u(k+N_u-1)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} \end{bmatrix}_{[\mathrm{Nux}\,Nu]}. \tag{9}$$

Once the individual elements of the gradient have been calculated, they are assimilated to zero. As a result, a new system of equations appeared, which can be solved taking into account the control effects $u(k)$, $u(k+1)$, .., $u(k+N_u+1)$:

$$\frac{\partial J[k,U(k)]}{\partial u(\mathrm{k})} = -2\hat{e}(k+N_1)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_1)}{\partial u(\mathrm{k})} - ... - 2\hat{e}(k+N_2)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_2)}{\partial u(\mathrm{k})} + \tag{10}$$
$$+2\lambda\Delta u(k) - 2\lambda\Delta u(k+1) = 0$$

$$\frac{\partial J[k,U(k)]}{\partial u(\mathrm{k}+1)} = -2\hat{e}(k+N_1)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_1)}{\partial u(\mathrm{k}+1)} - ... - 2\hat{e}(k+N_2)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_2)}{\partial u(\mathrm{k}+1)} + \tag{11}$$
$$+2\lambda\Delta u(k+1) - 2\lambda\Delta u(k+2) = 0$$

$$\frac{\partial J[k,U(k)]}{\partial u(\mathrm{k}+\mathrm{N}_u-2)} = -2\hat{e}(k+N_1)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_1)}{\partial u(\mathrm{k}+\mathrm{N}_u-2)} - ... -$$
$$-2\hat{e}(k+N_2)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_2)}{\partial u(\mathrm{k}+\mathrm{N}_u-2)} + 2\lambda\Delta u(k+N_u-2) - 2\lambda\Delta u(k+N_u-1) = 0, \tag{12}$$

$$\frac{\partial J[k,U(k)]}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} = -2\hat{e}(k+N_1)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_1)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} - ... -$$
$$-2\hat{e}(k+N_2)\frac{\partial\hat{y}(\mathrm{k}+\mathrm{N}_2)}{\partial u(\mathrm{k}+\mathrm{N}_u-1)} + 2\lambda\Delta u(k+N_u-1) = 0. \tag{13}$$

This system of equations can be solved very simply, starting with the last equation from which the control action $\Delta u(k+N_u-1)$ is calculated. The resulting value is replaced in the previous equation and determines $\Delta u(k+N_u-2)$. The whole sequence of control actions of control within the control horizon is calculated in a similar way [5].

For the neuro-fuzzy generalized predictive controller described above, it is customary to have four inputs, and each of them should be blurred using three Gaussian sets. One of its main drawbacks is the large number of fuzzy rules under which the forecasting model works. The number of these rules is determined by the expression $N = m^p$ and, therefore, in this case, the number of rules is 81. This means that during training, this model has parameters, which makes it practically unsuitable for working in real time, especially for processes with rapidly changing dynamics. Therefore, it is necessary to look for new nonlinear neuro-fuzzy models that work with a reduced number of fuzzy rules and at the same time provide high prediction accuracy. In addition to the model, the performance of this slider can be improved by incorporating 2nd row gradient algorithms in the optimizer. Corresponding adjustment can also affect the control quality of the nonlinear neuro-fuzzy general predictive controller. A two-level decision-making system for the selection of current technological modes and control of technological parameters of a catalytic cracking unit is based on soft computing technology [6,7].

The first level is intended to determine the degree of conversion of raw materials, determined by the value of the ratio of gas consumption to gasoline $(x_1)$, the total depth of gasoline and gas extraction as a percentage of raw materials $(x_2)$, the qualitative characteristics of the raw materials, i.e. percentage of distillation up to 350ºC $(x_3)$ and the degree of coking of the catalyst $(x_4)$ of such values of the temperature of the middle of the reactor $(y_1)$, the circulation rate of the catalyst $(y_2)$ and the weight rate of the feedstock $(y_3)$, which ensure the achievement of a close to optimal total yield of the target products of the installation. For this, the values of the initial boiling point of the raw material, coking of the catalyst and the aforementioned controlled parameters, output products of the installation, etc., measured by them and determined in the laboratory, are sent to the database (DB) of the system, where information about the state of the installation is stored. The central node is a fuzzy knowledge base (FKB), which is a set of cause-and-effect relationships between the input parameters of the installation $x_i, i=\overline{1,4}$ and the control parameters $y_i, i=\overline{1,3}$ formalized as products with a design "IF ..., THEN ... ELSE". The current values $x_i, i=\overline{1,4}$ from the database, after fuzzification in block F, are sent to the FKB. On the basis of this information, the inference block (IB), intended for making decisions on the installation mode, determines the current values $y_i, i=\overline{1,3}$. These values are the tasks for the automatic control systems (ACS) of the reactor temperature, the catalyst circulation rate and the weight velocity of the feedstock. After defuzzification in the DF block, they are transmitted as a task $g_{y_1,}g_{y_2,}g_{y_3}$ to the above control systems.Thus, the first level of the system provides in real time a close to optimal static mode of the installation according to the criterion of maximizing the total selection of the target products of the installation. It is shown that its dynamics varies within wide limits, in particular, the transfer coefficient along the reactor temperature control channel can vary within 0.6-10°C/t/u, the delay time is within $2min \le t \le 3{,}4min$.

The input influences of the object $U_1$ (regenerator temperature), $U_2$ (catalyst consumption), $U_3$ (raw material consumption), arriving at the input of the object, are simultaneously fed to the neural identifier, at the output of which the values of the controlled parameters $y_i^U, i=\overline{1,3}$. These values of the outputs of the neural identifier are compared with the current values of the corresponding outputs of the object $y_i, i=\overline{1,3}$. The obtained predicted errors $e_{y_1}^{pr} = g_{y_1} - y_i^U, i=\overline{1,3}$ serve as information for training the neural network of the identifier in the "off-line" mode.

After training the identifier, it is necessary to read the predicted (predictive) values of the object outputs $y_i^{pr} = y_i^U, i=\overline{1,3}$, which are compared with the regime values obtained at the first level of the system, i.e. controlled parameters $g_{y_i}, i=\overline{1,3}$. The received errors $e_{y_1}^{pr} = g_{y_1} - y_i^U, i=\overline{1,3}$ serve as information for training in the "on-line" mode of the neuro-fuzzy multidimensional controller. In order to compensate for the residual errors of the predicative system and ensure the stability of the synthesized control system, the object is closed by feedback on the current values of its outputs, which $y_i, i = \overline{1,3}$ are compared with their specified values and errors $e_{y_1}^{pr} = g_{y_1} - y_i^U, i = \overline{1,3}$ after defuzzification are fed to the multidimensional neuro-fuzzy controller. After defuzzification, the control parameters calculated on the basis of fuzzy “IF ..., THEN” rules are sent to the actuators in the form of clear signals.

## Conclusion

Within the framework of the methodology for creating Advanced Process Control Systems APC - advanced control systems, an approach is proposed to the implementation of decision support systems for operational predictive control of complex technological processes, based on soft computing technology and neuro-fuzzy models of short-term operational prediction with the Takagi-Sugeno mechanism and in in the form of a two-level hierarchical structure. At the first level of the control hierarchy, it is proposed to solve the problem of determining the quasi-optimal or rational technological mode of a statically investigated object on the basis of its fuzzy production mathematical model. At the second stage of the hierarchy of operational-predictive control, the problems of predictive control of the parameters of the catalytic cracking of oil are solved taking into account its changing dynamic characteristics. Computer simulation of the proposed system of operational and predictive control of the catalytic cracking of oil as a whole and its individual units and blocks has been carried out, and its software implementation has been carried out with reduced computational complexity.

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