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Development of a linguistic model of a reforming unit of a catalytic reforming plant

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Abstract. The influence of the main parameters of the reforming process on the quantity and quality of the produced product - catalyst - has been investigated. On the basis of the proposed linguistic modelling algorithm, a linguistic model has been built that describes: the effect of the temperature of the reforming reactor on the yield of catalyst and the stability of the catalyst. The possibility of constructing a linguistic model that estimates the influence of the feed rate of raw materials on the quantity and quality (octane number) of catalyst, a component of motor fuel, has been shown.

1.　　Introduction

When developing mathematical models of complex technological objects, problems of uncertainty can often arise due to the random or fuzzy nature of the initial information about the functioning of the object. This leads to the complication of the development of object models by traditional mathematical methods. If the uncertainty is caused by the randomness of the measured information, then the models can be built on the basis of probabilistic methods and experimental-static approaches [1, 2]. In this case, the parameters must be quantitatively measurable, the object must be statistically stable in order to be able to carry out the experiment many times under the same conditions, i.e. the axioms of the probability theory [3] must be fulfilled [3]. Then, based on the processed static data, it will be possible to develop models based on experimental and statistical methods. But in practice, some important production indicators, technological parameters that must be taken into account in models, may be difficult to quantify or not measurable. Such indicators and parameters can be easily assessed by a human operator, production personnel, a decision-maker (DM) who have the relevant knowledge and extensive experience on the object under study. The decision maker on the basis of his experience, knowledge and intuition, i.e. on the basis of a certain logical model, which was formatted by him during a long observation over the work of an object and in the process of managing it, he can effectively manage quantitatively difficult to describe objects [4]. Therefore, methods using fuzzy information in the form of knowledge, experience and intuition of specialists - experts, decision makers have recently become a more effective and expedient approach to the development of models for quantitatively difficult to describe objects. At the same time, methods of expert assessment and the theory of fuzzy sets are used to collect, formalize, process and use fuzzy information of a verbal nature. Currently, the demand in the world market is growing rapidly, incl. and in the domestic market of the Republic of Kazakhstan for

high-quality, environmentally friendly motor fuel, which is produced at catalytic reforming units of oil refineries. But many such installations are characterized by the fuzziness of some of the initial information and function in a fuzzy environment. Therefore, solving the problems of developing models of catalytic reforming units on the basis of available fuzzy information is an urgent task of science and oil refineries.

The purpose of this work is to develop a linguistic model of the reforming unit of a catalytic reforming unit in a fuzzy environment, which is characterized by fuzzy initial information.

2.   Literature review

There are numbers of research works devoted to the development of mathematical models under conditions of uncertainty and lack of initial information [1, 2, 4, 5]. In works [1, 2], methods of developing mathematical models of objects in terms of the probabilistic nature of the initial information are considered. In these works, uncertainty problems are solved on the basis of probabilistic methods and methods of mathematical statistics. In works [4, 5], an approach to solving the information deficit is proposed through the systematic use of available information of a different nature, incl. random and fuzzy. In this case, the fuzzy information is preliminarily transformed into a set of clear information with the help of a set of level α, which then makes it possible to apply conventional methods. But such a solution to the problem of the fuzzy initial information leads to the loss of a significant part of the original fuzzy information, respectively, to a decrease in the adequacy of the model. To reduce the loss of the collected fuzzy information and improve the adequacy of the developed model, the number of α slices can be increased, but this leads to an increase in the dimension of the problem and complication of its solution. The issues of collecting, processing and using fuzzy information when creating a knowledge base are discussed in works on methods of expert assessment, for example, in [6, 7]. And methods of processing fuzzy information, fuzzification procedures, carrying out various operations and processing fuzzy information and defuzzification were investigated in [8, 9]. These works describe in more detail the methodology for constructing and identifying fuzzy models with clear values of the input parameters and fuzzy values of the output parameters of the object. However, in the works analyzed, the methods and procedures for constructing a linguistic model are insufficiently considered, when both the input and output parameters of the object are fuzzy and are described by linguistic variables. Therefore, this work explores and considers the development of a linguistic model in more detail and proposes an algorithm for constructing a linguistic model.

3.   Research methodology

In order to develop a model, the influence of the main parameters of the reforming unit of the catalytic reforming unit LG-35-11 / 300-95 and their influence on the technological process of production of high-octane components of motor fuels were investigated. Based on the results obtained, the structure of the model of technological units of the reforming unit of the LG-35-11 / 300-95 unit is identified. The influence of the following main parameters and indicators on the reforming process has been investigated:

1. Reactor temperature. The temperature maintained in the catalyst bed of the reforming unit is the main control parameter that is used by the process operator to obtain a product of a given quality. Platforming catalysts can operate over a wide temperature range without causing significant deviations from the desired yield and catalyst stability. However, very high temperatures above 543 °C can lead to thermal reactions that will reduce the platform ate yield and catalyst stability [10]. To determine the temperature in the reactor, two indicators can be used: the weighted average temperature at the reactor inlet (WATRI) and the weighted average temperature of the catalyst bed (WATCB). These values can be calculated as follows [11]:

$WATRI = TW_{cb} \cdot TV_c,$

where $TB_k -$ is the total weight of the catalyst fractions in the bed; $TW_{cb} -$ temperature value at the entrance to the catalyst bed.

$WATCB = TW_{cb} \cdot TA_r,$

where $TV_c -$ is the value of the average temperature at the inlet and outlet of the reactor.

2. Feed rate of raw materials. Feed rate measures the amount of feed that is passed through a given amount of catalyst per unit of time. If the hourly volumetric productivity of the raw material and the volume of the loaded catalyst are known, then the volumetric feed rate can be found, but if the corresponding weight indicators are known, then the weight feed rate of the raw material can be determined.

The feed rate of the raw material has a decisive influence on the quality of the product (eg octane number). The higher the feed rate, the lower the octane number (ON), or the fewer reactions will occur at a given WATRI. At very low feed rates, thermal cracking reactions are accelerated resulting in a decrease in platform ate entry. Since the upper limit of the feed rate is not limited, in order to obtain a product of a given quality, it is necessary to increase the temperature, which in turn can also accelerate unwanted thermal reactions leading to a decrease in the selectivity of the process.

3. Pressure in the reactor. The pressure in the reactor is the most accurately determined value, as is the pressure in the catalyst bed. Since about 50% of the volume of the loaded catalyst is concentrated, as a rule, in the last reactor, the most accurate value will be the pressure at the inlet to the last reactor R-4. The pressure in the separator as an operating parameter is a limiting value, since the pressure drop from reactor to reactor can vary significantly, and even in the same reactor, the pressure drop will vary significantly with changes in feed throughput, velocity of circulating hydrogen-containing gas, its density, etc.

The pressure in the reactor influences the platforming unit product yield, the required temperature and the stability of the catalyst. With a decrease in the pressure in the reactor, the yield of platforming and hydrogen will increase, the temperature required to obtain a given quality of products will decrease, and the inter-regenerative life of the catalyst will decrease (the rate of coking of the catalyst will increase).

4. Hydrogen / feed ratio. The hydrogen / feed ratio (H2 / feed) is defined as the quotient of separating the number of moles of circulating hydrogen by the number of moles of naphtha loaded into the unit. Recycling hydrogen during platforming is essential to maintain catalyst stability. In the process of recirculation, the reaction products and condensed substances are washed off the catalyst surface, and hydrogen is delivered to its liberated active centers. Increasing the H2 / feed ratio will accelerate the passage of the naphtha through the reactor and provide more heat for endothermic reactions. The end result of this will be an increase in stability along with a small positive effect on yield or product quality.

5. Properties of processed raw materials. The properties of raw materials, which are one of the essential issues when discussing technological parameters, including fractional composition: start of boiling; 50% boiling point (distillation); content % (vol.) of paraffin (P) and naphthenic (N).

Raw materials with a low boiling point below 77 $^\circ$ C usually contain significant amounts of C_5 and higher hydrocarbons. The pentanes in the feed will not be able to convert to aromatic hydrocarbons, and therefore, when passing through the reaction zone, they undergo only isomerization reactions if cracked into light gases. Due to their low octane number, they reduce the octane performance of the entire platform ate as a whole and lead to the need to maintain a more rigorous platforming process than expected in the case of C_4 reforming and higher.

The low-end boiling point feeds contain high concentrations of C_6 and C_7, which are the most difficult to reformate. High end boiling point feed stocks lead to rapid catalyst coking, and they also promote high end boiling platforming.

To develop a linguistic model of the reforming unit of a catalytic reforming unit, which evaluates the influence of the reactor temperature on the volume of production and catalyst stability, the above research results are used, as well as methods of expert assessment and theories of fuzzy sets [6, 8, 9, 12].

4.   Research results

As a result of the analysis and generalization of possible approaches to modelling complex objects with indistinct initial information, an algorithm for the synthesis of models of technological objects in

conditions of fuzzy input and output parameters has been developed, which uses the logical rules of conditional inference and allows you to build linguistic models in a fuzzy environment. Thus, the proposed algorithm takes into account the fuzziness of the input $\tilde{x}_i, i = \overline{1,n}$ and output $\tilde{y}_j, j = \overline{1,m}$ parameters. The algorithm consists of the following main points, which are described in more detail in the previously published works of the authors [12, 13].

4.1   *Linguistic modelling algorithm*

Step 1. Select the input $\tilde{x}_i \in \tilde{A}_i, i = \overline{1,n}$ and output $\tilde{y}_j \in \tilde{B}_j, j = \overline{1,m}$ parameters of the object necessary for building the model, which are linguistic variables ($\tilde{A}_i \in X, \tilde{B}_j \in Y$ fuzzy subsets, X, Y universal sets).

Step 2. On the basis of expert procedures, evaluate the parameter values $\tilde{x}_i, \tilde{y}_j$ and construct a term-set $T(X, Y)$.

Step 3. Construct membership functions of fuzzy parameters $\mu_{\tilde{A}_i}(\tilde{x}_i), \mu_{\tilde{B}_j}(\tilde{y}_j)$.

Step 4. Build a linguistic model of the system and formalize fuzzy mappings that determine the relationship between $\tilde{x}_i$ and $\tilde{y}_j : R_{ij}$.

Step 5. Determine the fuzzy values of the input parameters of the object and select their numerical values from the fuzzy set of solutions [14].

Step 6. Check the model adequacy condition: $R = \min \sum_{j=1}^{m} (\tilde{y}_j^M - \tilde{y}_j^R) \le R_D$, where R the adequacy criteria; $\tilde{y}_j^M, \tilde{y}_j^R$, the values of the output linguistic variables obtained on the model and their real values, assessed by experts; R_D acceptable deviations of the criteria. If the adequacy condition is met, then the model is recommended for use in optimization and object management; otherwise, determine and return to the previous points to refine the model.

Development of a linguistic model of the catalytic reforming process based on the proposed algorithm.

To determine the optimal temperature of the reforming process on the basis of the linguistic modelling algorithm proposed above, the logical rule of conditional inference and the knowledge base, a linguistic model has been built that describes the effect of the temperature of the reforming reactor $\tilde{x}$ on the yield of catalyst, i.e. the value of the volume of production $\tilde{y}_1$ and the value of the stability of the catalyst $\tilde{y}_2$.

This model implements the following linguistic dependency with structure:

«IF $\tilde{x}$ low, THEN output $\tilde{y}_1$ low, stability $\tilde{y}_2$ below normal,

IF $\tilde{x}$ average, THEN $\tilde{y}_1$ average, $\tilde{y}_2$ normal,

IF $\tilde{x}$ high, THEN $\tilde{y}_1$ above average, $\tilde{y}_2$ above normal,

IF $\tilde{x}$ very high, THEN $\tilde{y}_1$ below the average, $\tilde{y}_2$ below normal »,   (1)

where $\tilde{x}$ – reactor temperature, $\tilde{y}_1$ – volume of catalyst from the reactor, $\tilde{y}_2$ – catalyst stability.

The presented linguistic model for assessing the influence of the reactor temperature on the volume of the produced product and the stability of the catalyst, for ease of perception, will be presented in tabular form (table 1).

Table 1. Rule base for assessing the effect of temperature on production volume and catalyst stability

Input fuzzy parameter: $\tilde{x}$ reformer temperature		Output fuzzy parameters:	
		Product volume $\tilde{y}_1$	Catalyst stability $\tilde{y}_2$
1	Low	Low	Below normal
2	Average	Average	Normal
3	High	Above average	Above normal
4	Very high	Below the average	Below normal

On the basis of expert procedures and applying the analytical dependence proposed in work [15], membership functions are determined that describe fuzzy sets:

$$\mu_{\tilde{A}_1}(\tilde{x}) = \exp\left|(x - 485)^{0,4}\right| \text{ - low reactor temperature;}$$

$$\mu_{\tilde{A}_2}(\tilde{x}) = \exp\left|(x - 495)^{0,5}\right| \text{ – average reactor temperature;}$$

$$\mu_{\tilde{A}_3}(\tilde{x}) = \exp\left|(x - 520)^{0,6}\right| \text{ – high reactor temperature;}$$

$$\mu_{\tilde{A}_4}(\tilde{x}) = \exp\left|(x - 545)^{0,7}\right| \text{ – very high reactor temperature;}$$

$$\mu_{\tilde{B}_1^1}(\tilde{y}_1) = \exp\left|(y_1 - 70)^{0,4}\right| \text{ – low catalysis yield;}$$

$$\mu_{\tilde{B}_2^1}(\tilde{y}_1) = \exp\left|(y_1 - 67)^{0,5}\right| \text{ – below average catalysis yield;}$$

$$\mu_{\tilde{B}_3^1}(\tilde{y}_1) = \exp\left|(y_1 - 72)^{0,6}\right| \text{ – average yield of catalyst;}$$

$$\mu_{\tilde{B}_4^1}(\tilde{y}_1) = \exp\left|(y_1 - 75)^{0,7}\right| \text{ – above average catalysis yield;}$$

$$\mu_{\tilde{B}_1^2}(\tilde{y}_2) = \exp\left|(y_2 - 85)^{0,3}\right| \text{ – catalyst stability below normal;}$$

$$\mu_{\tilde{B}_2^2}(\tilde{y}_2) = \exp\left|(y_2 - 90)^{0,5}\right| \text{ – catalyst stability is normal;}$$

$$\mu_{\tilde{B}_3^2}(\tilde{y}_2) = \exp\left|(y_2 - 95)^{0,7}\right| \text{ – catalyst stability above normal.}$$

Applying the structure of the linguistic model in equation (1) and modifying it in relation to our conditions, on the basis of the algorithm developed above, the following linguistic model was obtained:

IF $\tilde{x} \in \tilde{A}(nz)$, THEN $\tilde{y}_1 \in \tilde{B}_1(nz)$, $\tilde{y}_2 \in \tilde{B}_2(nn)$,

IF $\tilde{x} \in \tilde{A}(sr)$, THEN $\tilde{y}_1 \in \tilde{B}_1(sr)$, $\tilde{y}_2 \in \tilde{B}_2(nr)$,

IF $\tilde{x} \in \tilde{A}(vs)$, THEN $\tilde{y}_1 \in \tilde{B}_1(vs)$, $\tilde{y}_2 \in \tilde{B}_2(vn)$,

IF $\tilde{x} \in \tilde{A}(ovs)$, THEN $\tilde{y}_1 \in \tilde{B}_1(ns)$, $\tilde{y}_2 \in \tilde{B}_2(nn)$.

where *nz, nn, sr, nr, vs, vn, ovs, ns* – fuzzy variables describing, respectively, the concepts of "low", "below normal", "average", "normal", "high", "above normal", "very high", "below average"; $\tilde{x}$, $\tilde{y}_1$, $\tilde{y}_2$ – linguistic input and output variables describing, respectively, the temperature of the reactor, the volume of catalyst and the stability of the catalyst; $\tilde{A}$, $\tilde{B}_j$, $j - 1, 2$ – fuzzy subsets characterizing $\tilde{x}$, $\tilde{y}_1$, $\tilde{y}_2$.

In accordance with clause 4 of the above algorithm, fuzzy mappings are formalized that determine the relationship between $\tilde{x}$ and $\tilde{y}_j$, $j-1,2 : R_{ij}$, the qualitative values of the object's parameters and their numerical values from the fuzzy set of solutions are determined by the formula:

$$\tilde{y}_j^{**} = \arg \max_{\tilde{y}_j^*} \mu_{\tilde{B}_j} \left(\tilde{y}_j^* \right), \text{ where } \mu_{\tilde{B}_j} \left(\tilde{y}_j^* \right) - \text{membership functions of output variables (fuzzy solution).}$$

5.   The discussion of the results

The proposed linguistic modeling algorithm is heuristic and is implemented in a human-computer dialogue mode. At the same time, a person is a specialist-expert in the subject area, a decision-maker for an object. In steps 1 and 2, with the help of the decision maker, experts select more informative input and output fuzzy parameters that affect the operation of the facility and assess the quantity and quality of products. A term-set is determined that describe changes in fuzzy parameters, that is, linguistic variables.

In step 3, to construct a membership function, for example, the output parameters of an object, based on practical experience, we can recommend applying the following exponential dependence [13]:

$$\mu_{\tilde{B}_j} \left(\tilde{y}_j \right) = \exp \left(Q_{B_j}^P \left| \left(y_j - y_j^{md} \right)^{N_{B_j}^P} \right| \right).$$

In this formula p – quantum number; $Q_{B_j}^P$ – parameter characterizing the degree of fuzziness, its value is identified when constructing the membership function; $N_{B_j}^P$ – coefficient that allows you to more accurately approximate the graph of the membership function; y_j^{md} – a fuzzy variable that more closely matches the selected term and is defined by the expression $\mu_{\tilde{B}_j}^P \left(y_j^{md} \right) = \max_j \mu_{\tilde{B}_j}^P \left(y_j \right)$.

In this step, the membership function can be constructed using typical functions from the Fuzzy Logic Toolbox application of the Matlab system [16]. In step 4, the linguistic model of the object is built based on processing expert information and applying the methods of fuzzy logic [17]. For convenience, the linguistic model can be drawn up in the form of a table, in which each line indicates the possible values of the linguistic input parameters $\tilde{x}_i$ and the values of the corresponding output parameters $\tilde{y}_j$. In this case, the table is filled using the term-set defined above in step 2. Thus, based on such a model, a fuzzy mapping R_{ij} is formed, which determines the relationship between the input and output linguistic parameters. To formalize such a fuzzy mapping, you can use the logical evaluation method. In this case, based on expert information, a detailed description of all possible cases is given using the term-set of input and output linguistic variables. This description, called a linguistic model, consists of a nested set of logical rules of the form:

$$IF \ \tilde{x}_1 \in \tilde{A}_1 \left(\tilde{x}_2 \in \tilde{A}_2 \left(..., \left(\tilde{x}_n \in \tilde{A}_n \right) \right), ..., \right), \ THEN \ \tilde{y}_j \in \tilde{B}_j; \ j = \overline{l, m},$$

where $\tilde{x}_i, i = \overline{1, m}, \tilde{y}_j, j = \overline{1, m}$ – the corresponding input and output linguistic variables of the object, $\tilde{A}_i, \tilde{B}_j$ – fuzzy subset that describes linguistic variables $\tilde{x}_i, \tilde{y}_j$.

If both the input and output parameters of the object are fuzzy, then based on the rules of compositional inference $\tilde{B}_j = \tilde{A}_i \circ \tilde{R}_{ij}$, the fuzzy values of the output parameters of the object are determined by the formula:

$$\mu_{\tilde{B}_j}^P \left(\tilde{y}_j^* \right) = \max_{x_i \in X_i} \left\{ \min \left[\mu_{\tilde{A}_i}^P \left(\tilde{x}_i^* \right), \mu_{\tilde{R}_{ij}}^P \left(\tilde{x}_i^* \tilde{y}_j \right) \right] \right\}, \tag{2}$$

where $\mu_{\tilde{B}_j}^P \left(\tilde{y}_j^* \right)$ – membership function of fuzzy output parameters on the p-th quantum.

In step 5, the choice of numerical, that is, clear values of the output parameters of the object $\tilde{y}_j^{**}$ is determined from the set of fuzzy solutions of equation (2) by the formula:

$$\tilde{y}_j^{**} = \arg\max_{\tilde{y}_j^*} \mu_{\tilde{B}_j}^* \left(\tilde{y}_j^* \right).$$

Similarly, to the obtained linguistic model equation (1), it is possible to synthesize other linguistic models. For example, a linguistic model describing the influence of the feed rate on the quantity and quality (octane number) of catalyst (the target reforming product). Such a linguistic model describes the logical conclusion "The higher the feed rate, the lower the octane number and the higher the catalyst yield".

6.   Conclusion

The paper presents the results of a study on the development of a linguistic model of quantitative hard-to-describe objects on the example of a reforming unit of a catalytic reforming unit.

Based on the results obtained, the following main conclusions can be drawn:

i)   The influence of the main parameters and parameters of the object on the reforming process has been investigated, which include: the temperature of the reforming reactor; feed rate of raw materials; reformer pressure; hydrogen / feed ratio; properties of processed raw materials.

ii)   A heuristic algorithm for linguistic modeling has been developed, which makes it possible to synthesize a linguistic model of complex objects in a fuzzy environment in an interactive mode. A more detailed description of the main steps of the proposed algorithm is given.

The novelty of the proposed algorithm for the synthesis of a linguistic model is the integrated use of knowledge, experience, human intuition to formalize and process fuzzy information of a verbal nature and the capabilities of a computer. Such a human-machine system, due to the emergence of this system, makes it possible to effectively solve the problems of modeling complex objects in a fuzzy environment.

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