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Hybrid Models of Atmospheric Block Columns of Primary Oil Refining Unit Under Conditions of Initial Information Deficiency

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Abstract: This work is devoted to the study and solution of the problems of modeling complex objects on the example of the atmospheric block of the primary oil refining unit, associated with the deficit and fuzziness of the necessary initial information. Since many real technological objects of oil refining and other industries are often characterized by a deficit and fuzziness of the necessary information for their study, modeling, and optimization, this work allows solving an urgent scientific and practical problem. An effective method has been proposed that allows, based on a system approach, expert assessment methods, theories of fuzzy sets, and available information of various natures to develop hybrid models of complex objects in conditions of deficiency and fuzzy initial information. Based on the proposed hybrid method and available statistical and fuzzy information, effective hybrid models of atmospheric block columns of the primary oil refining unit were developed. In this case, statistical models were developed based on experimental and statistical data. With crisp input, mode parameters, and fuzzy output parameters, atmospheric block fuzzy models based on the proposed method, determining the quality of the manufactured products, were developed. Moreover, with the fuzzy input, mode, and output parameters of the atmospheric block columns, linguistic models based on the methods of expert assessments, logical rules of conditional inference, and the proposed method, assessing the quality of the produced gasoline, were developed. The linguistic models developed in Fuzzy Logic Toolbox allow for the assessment of the quality of gasoline from the atmospheric block depending on the content of chloride salts and the mass fraction of sulfur in the raw material. The results obtained using the proposed modeling method show their advantages in comparison with known modeling methods.

Keywords: technological systems; hybrid model development method; fuzzy information; atmospheric vacuum block; sulfur production section; decision maker; rule base

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1. Introduction

Technological processes of primary processing of oil, sulfur production, and other processes of oil refining, petrochemistry, and other industries take place in complex technological systems (TS), consisting of interconnected units [1–3]. The main interconnected aggregates of the atmospheric block of the primary oil refining unit include the oil stripping rectification column and the atmospheric column. The products of the atmospheric block of the primary oil refining unit are straight-run gasoline (initial boiling point fraction (IBP)—180 °C); diesel fuel (fraction 180–350 °C); fuel oil (fraction above 350 °C); and hydrocarbon gas (C1–C4), obtained from crude oil [4,5]. In the process of researching and modeling such complex objects, problems of uncertainty arise due to the deficit and fuzziness of the initial information for the development of models. The proposed work is aimed at researching and solving these problems of modeling complex objects using the example of atmospheric block columns.

To create a decision support system for managing primary oil refining and sulfur production processes and selecting an effective operating mode for the TS in which they occur, it is necessary to develop a set of effective models of their main aggregates. For example, for the atmospheric block of the primary oil refining unit, it is necessary to develop a set of models of the main columns: the rectification column C-1 and the atmospheric column C-2. In practice, the development of mathematical models of these columns is complicated by the shortage and fuzziness of the initial information necessary for creating their models [6]. In production conditions, it is very difficult or impossible to determine the fractional composition of the processed oil, the values of some important input, and the operating parameters of the specified columns, which affect their output parameters using measuring instruments.

In production, such quantitatively difficult-to-describe objects are often well managed by the operator—the decision-maker (DM), who manages it based on their experience, knowledge, and intuition. Their experience, knowledge, and intuition are expressed in natural language as fuzzy information. Based on expert assessment methods and fuzzy set theories, it is possible to collect, formalize, and use such fuzzy information in order to describe the operating modes of fuzzy-described objects and develop their models. In this regard, at present, the issues of developing adequate models of complex, quantitatively difficult-to-describe objects, such as C-1 and C-2, characterized by a shortage and fuzziness of the initial information, is a relevant scientific and practical problem. In this study, for an effective solution to this problem in conditions of shortage and fuzziness of the initial information, an approach is proposed based on the use of available statistical and fuzzy information from DMs and subject matter expert specialists.

Let us present the results of the analysis of works on the research topic, devoted to the issues of development of models of complex, production objects and technological processes. In research works [7–20], various approaches to the development of models and modeling of technological objects in various conditions are proposed, including the use of fuzzy information. In particular, in studies under the supervision of Kafarov [7,8], Guseinov [9], Zhorov [10], and Zahedi [11], deterministic models of the main processes of various industries, occurring in technological units, were developed based on theoretical information and the kinetics of processes. The advantage of the deterministic models of typical units and processes of various industries proposed in these studies is their universality and theoretical validity since they are developed on the basis of fundamental laws of nature (conservation of mass and energy, etc.). The disadvantage of deterministic models for complex technological objects, such as the studied columns C-1 and C-2, is the impossible or very complex development, which, ultimately, becomes economically inexpedient. This is due to the fact that such complex objects are characterized by a shortage and/or lack of the necessary theoretical information for the development of deterministic models; moreover, they are characterized by the fuzziness of the initial information. At the same time, the adoption of various assumptions and the idealization of the operating conditions of complex objects for the development of deterministic models with a shortage, and fuzziness of the initial information leads to the receipt of inadequate, unsuitable models for practical application.

In the works of Bequette, Wen, Freedman, Douglas, Zhuang, and others [12–16], statistical approaches to the development and modeling of various objects are investigated. The proposed statistical models are suitable for modeling and optimizing the operating modes of complex objects for which it is impossible to develop deterministic models. The identification of such models is based on reliable statistical data on the condition and operation of objects. For this purpose, it is necessary to conduct multiple experiments to collect and process statistical data. But, for objects characterized by fuzziness, such as atmospheric block columns, for which it is impossible to measure some important parameters necessary for developing their models, the statistical approach is not applicable.

In practice, even with the theoretical possibility of collecting and processing the necessary statistical information, in production conditions, this may prove to be economically inexpedient and unprofitable. In these situations, it is necessary to develop mathematical models of production objects using available fuzzy information.

We first briefly review the methods and tools of Simulink 9.3 and Modelica 3.4, specially developed for the construction and study of complex multiphysical dynamic systems, which are used for physical modeling and simulation. Simulink is a signal flow-based modeling and simulation environment developed by MathWorks as a toolkit for the MATLAB system R2018b. Simulink is currently accepted as a standard for modeling and simulating controllers and systems based on signals of all types [17,18]. Modelica is an equation-based modeling language for physical systems, developed as an open-source language by the Modelica Association and used in a variety of modeling programs. The most well-known commercial programs using Modelica are Dymola, SimulationX, Wolfram SystemModeler, Modelon Impact, and MapleSim. OpenModelica is also a fairly mature open-source alternative [19,20].

Simulink and Modelica can be used to model and simulate dynamic systems described by differential-algebraic systems of equations. Simulink is implemented in the Matlab system and Modelica—in a suitable development environment such as Dymola. They have a graphical user interface in which complex systems can be modeled as a network of individual interconnected components, which increases the clarity and convenience for the user when modeling complex systems [21].

The authors of [22–25] investigated and proposed approaches to the development of models and control of objects based on them in conditions where some parts of the initial information are fuzzy, based on the application of expert assessment methods and fuzzy set theories. The proposed approaches to the development of models based on a set of α-level allow the development of fuzzy models with crisp values of the input, mode parameters, and fuzzy values of the output parameters of the object. But in these and other studies of model development based on fuzzy information, the problems of developing linguistic models under conditions of fuzzy input, mode, and output parameters of the object have not been investigated and solved. In addition, the analyzed and other studies on model development have not investigated the problems of developing a complex of interconnected process unit models, such as the C-1 and C-2 atmospheric block columns. This became the main motivation for this study. In this regard, the aim of the study is to create an effective method for developing hybrid models of complex objects such as the atmospheric block columns of the primary oil refining unit. Based on the proposed method, it is necessary to develop effective models of atmospheric block columns based on available statistical data and fuzzy information from subject area experts and specialists representing their knowledge, experience, and intuition.

Today, more effective modeling methods have become deep learning methods based on multilayer neural networks, which is a promising direction for artificial intelligence methods [26,27]. Deep learning methods are already successfully used for modeling and solving problems of pattern and speech recognition [28,29] in medicine [30], in industry [31,32], and in other areas. Deep learning methods have great potential in developing and training models used in oil refining process facilities. In this study, the authors used a systematic approach to develop a system of models of the main units of the atmospheric block of the primary oil refining unit under conditions of a deficit and fuzzy initial information. The proposed hybrid modeling method is based on the use of available statistical and fuzzy information based on experimental-statistical methods, expert assessment methods, and fuzzy set theories. In future studies, the authors plan to explore the possibility of using deep learning to develop models of oil refining facilities.

The performance advantages of the proposed hybrid approach to modeling technological objects based on statistical methods, expert assessment methods, and fuzzy set theories compared to other known fuzzy object models [23–25] are:

- the possibilities of the proposed system method to develop effective models of complex production facilities based on available statistical and fuzzy information;
- by using additional fuzzy information from subject area expert specialists, representing their knowledge, experience, and intuition, the proposed approach allows for the synthesis of more adequate models of complex production facilities in the presence of a shortage and fuzzy initial information;
- the combined use of experimental-statistical methods, expert assessment methods, and fuzzy logic allows the effect of synergy and the emergence of the system of methods used to be achieved.

To achieve the stated goal, the following research tasks are solved in the work:

- development of a method for synthesizing a set of statistical, fuzzy, and linguistic models of interconnected objects of complex systems based on available statistical and fuzzy information;
- on the basis of the proposed method to develop hybrid models of atmospheric block columns of the primary oil refining unit based on available experimental-statistical and fuzzy information from experts in the subject area. In this case, experimental-statistical data should be collected and processed based on active, and passive experiments and methods of mathematical statistics, as well as for the collection and processing of fuzzy information—methods of expert assessments and theories of fuzzy sets;
- to synthesize linguistic models for assessing the quality of gasoline from the atmospheric block outlet based on the proposed method, fuzzy information from experts, and the Fuzzy Logic Toolbox of the MATLAB system R2018b;
- to compare the obtained results of modeling the atmospheric block operating modes with known results and describe the advantages of the proposed hybrid approach to the development of models and modeling.

To solve the problems of developing models of fuzzy objects, in contrast to known approaches, we use a different approach based on methods of system analysis, expert assessments, and theories of fuzzy sets, which allow for the development of more effective models of objects in a fuzzy environment. The proposed method allows the development of more adequate models due to the maximum use of fuzzy information in the form of experience, knowledge, and intuition of DM and subject matter experts.

It is known that system analysis is used when the problem is difficult to formalize and involves a combination of many different formal and informal methods that may be contradictory. Thus, in the developed hybrid model, in general, the presence of deterministic models based on theoretical information and physical modeling is natural. But, in our case, physical modeling of the units of the rectification column C-1 and atmospheric column C-2 of the atmospheric block under study is very complex and impractical, and the required amount of theoretical information is missing [1,4,6,8]. Taking this difficulty into account, in addition to deterministic models, the hybrid model being created includes statistical, fuzzy, and linguistic models, which are developed on the basis of available and collected statistical data and fuzzy information from experts. Additional fuzzy information was obtained on the basis of expert assessment methods and processed using fuzzy set theory methods, which made it possible to build a meaningful and highly adequate model.

2. Object, Materials, and Methods

The object of the study is the C-1 and C-2 columns of the atmospheric block of the EDP-AT-2 Atyrau refinery primary oil refining unit, which is characterized by fuzzy initial information. The materials of the study are the process flow diagrams, description, and process regulations for the operation of the atmospheric block of the Atyrau refinery primary oil refining unit [4], as well as statistical data and fuzzy information about the state and modes of its operation. Figure 1 shows the process flow diagram of the atmospheric block, isolated from the general diagram of the EDP-AT-2 Atyrau refinery unit.

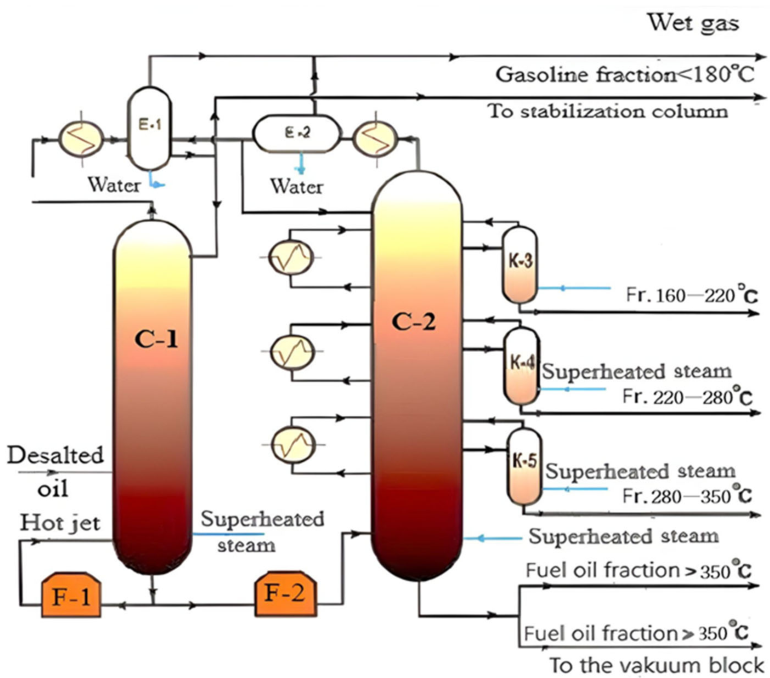


Figure 1. Process flow diagram of Atyrau refinery atmospheric block.

The feedstock of the atmospheric block of the primary oil refining unit is desalted oil from the EDP block. The feedstock heated to a temperature of 160–220 °C enters the rectification column C-1, where partial stripping and degassing occurs. The condensate of light fractions of gasoline is removed from the unit. The semi-stripped oil from the bottom of C-1 is heated in furnaces F-1 and F-2 to 360–385 °C and, in the vapor–liquid phase, enters the atmospheric column C-2. In column C-2, the oil is separated into different fractions due to the different temperature conditions at the levels of the column. From the top of the C-2 column, the mixture of gasoline, gas, and water vapor is sent via a slam line through condensers to the E-2 gas–water separator, where it is separated into gas, gasoline, and water. After cooling, the gas–gasoline–water mixture is sent via a bypass to the E-1 tank.

The gas from the E-2 gas–water separator enters the gas separator, from where the gas is sent to the fuel network.

To improve the stripping of light fractions, live steam is fed into the cube of column C-2, which is preheated in furnace F-1. To select narrow fractions of 180–220, 220–280, and 280–350 °C, their overflows into stripping columns K-3, K-4, and K-5, are provided, respectively, from which, after cooling, these fractions are removed from the unit. Fuel oil (fraction > 350) from the bottom of column C-2 is removed from the AT block.

The Flow diagram shown in Figure 1 is adapted for the atmospheric block of the Atyrau refinery primary oil refining unit and shows the processes of primary oil refining and production of different fractions of petroleum products. The graphical approach to optimization proposed in the work is used [33].

When developing mathematical models of interconnected columns C-1 and C-2 of the atmospheric block, due to the fuzziness of the requirements for the quality indicators of feedstock and product (gasoline) of the type "no more than" and "no higher" presented by the standard, problems arise in synthesizing their models. For example, the following basic fuzzy requirements are presented to the quality indicators of the feedstock of the atmospheric block according to the standard CT TOO 40319154-07-2008 [1]: content of chloride salts, mg/l "no more than 4"; mass fraction of sulfur, %, no more than 0.8".

Moreover, for types of gasoline from the atmospheric block outlet, according to CT TOO 40319154-13-2018, the following basic fuzzy requirements are imposed: end boiling point, °C, "not higher than 205"; residue and losses, %, "not more than 4.0".

Models for determining the volume of gasoline from the outlet of the atmospheric block depending on the input and operating parameters can be developed based on the experimental-statistical approach. And, to take into account the requirements for the quality indicators of gasoline, it is necessary to develop linguistic models that take into account the requirements of fuzzy constraints. In this regard, the methods used in developing models of interconnected columns C-1 and C-2 are statistical methods [13–16,34,35], methods of system analysis [36,37], methods of expert assessments, and theories of fuzzy sets [22,23,38–44].

Figure 2 shows flowcharts illustrating the processes of collecting data information and processing them, as well as developing, training, and testing the developed models for adequacy. Based on the flowcharts provided, we describe more detailed step-by-step instructions, including specific details of data collection, preliminary processing, model training, and validation.

In blocks (1)–(3), the processes of measurement, collection, and processing of statistical data on the operating modes of the objects of study are implemented. Data collection is carried out using appropriate measuring devices, and active experiments are carried out to collect the missing data based on the methods of mathematical planning of experiments. Methods of mathematical statistics and probability theory are used to process the collected statistical data.

In blocks (1)–(3), the processes of measurement, collection, and processing of statistical data on the operating modes of the objects of study are implemented. Data collection was carried out using appropriate measuring devices, and active experiments were carried out to collect the missing data based on the methods of mathematical planning of experiments.

In block (3), statistical models of a polynomial type are developed, the structure of which is identified on the basis of the method of sequential inclusion of regressors, and unknown parameters are identified on the basis of the modified least squares method. In parametric identification of models, the REGRESS software package 3.1 or MATLAB R2018b Curve Fitting Tool applications can be used, in which the least squares method is implemented programmatically.

In blocks (4)–(6), the processes of collecting fuzzy information from experts on fuzzy-described parameters characterizing the quality indicators of gasoline produced in the atmospheric block are implemented. In block (5), the collection of fuzzy information was carried out on the basis of expert assessment methods, which are then processed by methods of fuzzy set theories.

In block (6), based on the α-level set with crisp input and fuzzy output parameters of the object, linguistic models of the object are synthesized. If both the input and output parameters of the object are fuzzy, then, in block (6), based on the logical rules of conditional inference of the production model of knowledge representation, linguistic models of the object are synthesized. The resulting linguistic models describe the dependence of the quality of gasoline from the output of the atmospheric block (output parameter) on the fuzzy-described content of chloride salts and the mass fraction of sulfur in the raw material of the atmospheric column (input parameters).

In block (7), the adequacy of the developed statistical, fuzzy, and linguistic models is checked, and their validations are carried out. If the adequacy of the models is sufficient, then the obtained models are derived, and they are implemented in the form of programs for computer modeling and optimization of the operating modes of the atmospheric block (block (9)). If the adequacy of the models is lower than required, then training of the models is carried out and low adequacy is eliminated to increase the adequacy of the developed models. The cycles covering the processes in blocks (7) and (8) are repeated until the required level of adequacy of the developed models is achieved.

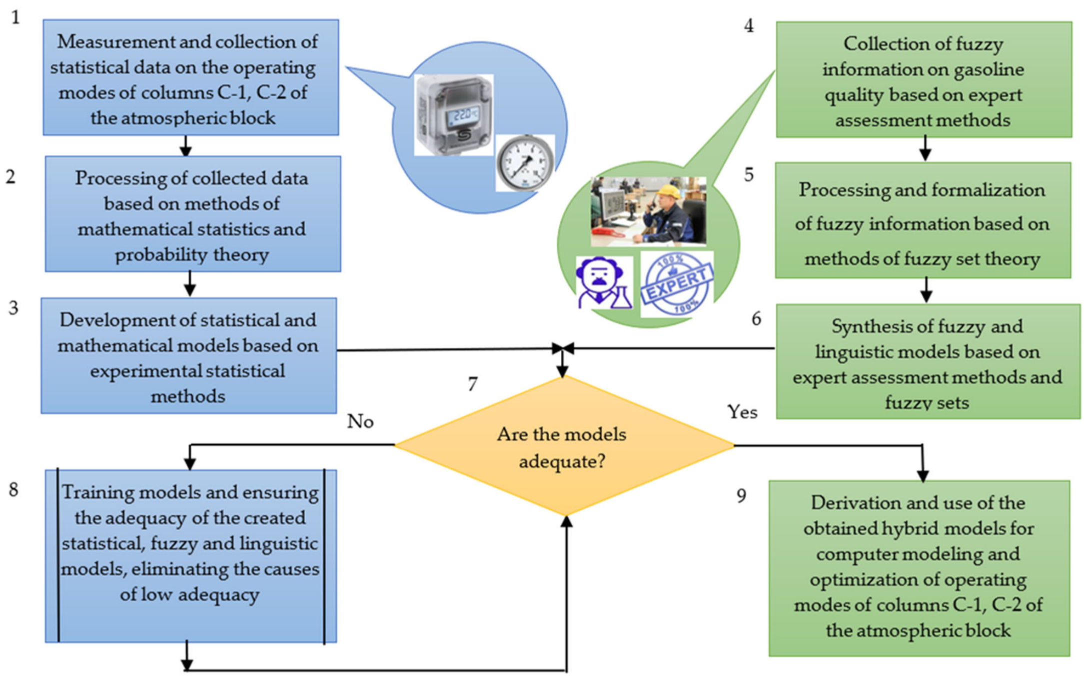


Figure 2. Flowcharts of processes of collection, data, information and their processing, development, and testing of developed models for adequacy.

In this paper, we propose a hybrid method for developing statistical, fuzzy, and linguistic models of complex objects characterized by a shortage and fuzziness of the initial information. The proposed method is based on the methodology of system analysis, experimental-statistical methods, as well as methods of expert assessments and theories of fuzzy sets, and it is used to develop models of columns C-1 and C-2 of the atmospheric block.

Method for Developing a Set of Statistical, Fuzzy, and Linguistic Models of Interconnected Aggregates Based on Available Statistical and Fuzzy Information

The proposed method consists of the following main points.

1. Based on system analysis, collect and process available statistical $x_i,\ i = 1, \ldots, n_1$ and fuzzy $\tilde{x}_i,\ i = n_1 + 1, \ldots, n$ information about the operating modes of interconnected objects of the technological system that affect the output parameters that characterize the quality of the object. Here and below, *i*—the index of input, mode parameters, n_1—the number of crisp input parameters, and *n*—the number of fuzzy input mode parameters of the modeled object. The output parameters of the object can also be crisp $y_j,\ j = 1, \ldots, m_1$ and fuzzy $\tilde{y}_j,\ j = m_1 + 1, \ldots, m$ assessed by DM and experts. Here and below, *j*—the index of output parameters, m_1—the number of crisp output parameters, and *m*—the number of fuzzy output parameters of the modeled object

2. Generate criteria $f_k,\ k = 1, \ldots K$ for selecting an effective type of model for each object of the technological complex, where *k*—criteria index, and *K*—total number of criteria.

3. For each object of the technological complex, based on the nature of the available initial information and the selection criteria $f_k,\ k = 1, \ldots K$, using expert assessment methods to determine the effective type of the model being developed.

4. If the initial reliable statistical information for an object is sufficient and, based on the results of expert assessment, the statistical model is preferable, then a statistical model is developed for this object based on the experimental statistical method. In general, the structure of the statistical model is defined as: $y_j = f_j(a_0,\ a_1, \ldots, a_{n_1}, x_1, \ldots, x_{n_1}),\ j = 1, \ldots, m_1$, where $a_1, \ldots, a_{n_1}$– identifiable model parameters. Then, to check the adequacy of the resulting model, go to point 14. Otherwise, go to the next point, point 5.

5. If the input and operating parameters of the object are crisp, and the output parameters are fuzzy, then, for it, based on the methods of expert assessment and the theory of fuzzy sets, go to point 15 to develop fuzzy models. If both the input operating parameters and the output parameters of the object are fuzzy, go to the next point to develop its linguistic variables.

6. Input and output fuzzy parameters of an object are described by linguistic variables $\tilde{x}_i \in \tilde{A}_i,\ \tilde{y}_j \in \tilde{B}_j, i = n_1 + 1, \ldots, n,\ j = m_1 + 1, \ldots, m$, where $\tilde{A}_i,\ \tilde{B}_j$—fuzzy subsets of universes *X* and *Y*.

7. Terms describing changes in linguistic variables are defined, and membership functions are constructed for them based on expert assessment methods $\mu^t_{\tilde{A}_i}(\tilde{x}_i)$, $i = n_1 + 1, \ldots, n, \mu^t_{\tilde{B}_j}(\tilde{y}_j),\ j = m_1 + 1, \ldots, m$.

8. A fuzzy mapping $\tilde{R}_{ij}$ is constructed, defining the relationships between the fuzzy input $\tilde{x}_i$ and output $\tilde{y}_j$ linguistic variables. For convenient calculation of $\tilde{R}_{ij}$, they are presented as a matrix of relationships using the membership function:

$$\mu_{\tilde{R}_{ij}}\left(\tilde{x}_i,\ \tilde{y}_j\right) = \min\left[\mu_{\tilde{A}_i}\left(\tilde{x}_i\right), \mu_{\tilde{B}_j}\left(\tilde{y}_j\right)\right], i = n_1 + 1, \ldots, n,\ j = m_1 + 1, \ldots, m. \quad (1)$$

The motivation for choosing Formula (1) when defining the fuzzy mapping was the well-known compositional rule of inference of fuzzy set theories, which is modified in this paper to solve the problem of synthesizing linguistic models. In Formula (1) min—means the operation of the intersection of the membership function of the input and output fuzzy parameters of the object, i.e., $\mu_{\tilde{A}_i}(\tilde{x}_i), \mu_{\tilde{B}_j}(\tilde{y}_j)$. Thus, according to the given expression (1), the membership function of the fuzzy mapping $\mu_{\tilde{R}_{ij}}(\tilde{x}_i,\ \tilde{y}_j)$ is determined according to the well-known rule of fuzzy set theory as the minimum value of the membership function of the input and output fuzzy parameters of the modeled object.

9. Based on the logical rule of inference, the structure of linguistic models of an object with fuzzy input and output parameters is generally synthesized with the involvement of DMs and experts in the form:

$$IF\ \tilde{x}_{n_1+1} \in \tilde{A}_1 \wedge \tilde{x}_{n_1+2} \in \tilde{A}_2 \wedge, \ldots, \wedge \tilde{x}_n \in \tilde{A}_n\ THEN\ \tilde{y}_j^M \in \tilde{B}_j, j = m_1 + 1, \ldots, m, \tag{2}$$

where $\wedge$—logical "and" meaning all statements are true; $\tilde{y}_j^M$, $j = m_1 + 1, \ldots, m$—fuzzy values of output parameters determined on the basis of the model.

To implement fuzzy rules (2), which are linguistic models, a production model of knowledge representation is used, since it is created on the basis of fuzzy expert information [39,40]. These linguistic models evaluate the influence of input and operational fuzzy parameters of an object in a fuzzy environment $\tilde{x}_i$, $i = 1, \ldots, n$ on its fuzzy output parameter $\tilde{y}_j^M$, $j = m_1 + 1, \ldots, m$.

10. Based on the compositional rule of inference of fuzzy set theories, fuzzy values of the output parameter of an object are determined: $\tilde{B}_j = \tilde{A}_i \circ \tilde{R}_{ij}$. For ease of application of this rule, the fuzzy values of the output parameters of an object based on the maximin product are determined by the membership function:

$$\mu_{\tilde{B}_j}\left(\tilde{y}_j^*\right) = \max\left\{\min_{\tilde{x}_i \in X}\left[\mu_{\tilde{A}_i}\left(\tilde{x}_i^*\right), \mu_{\tilde{R}_{ij}}\left(\tilde{x}_i^*, y_j^M\right)\right]\right\}, \tag{3}$$

where x_i^*—fuzzy values of input parameters estimated by experts. Then, the current values of input parameters can be determined by the formula $\mu_{\tilde{A}_i}(\tilde{x}_i^*) = \max_i \mu_{\tilde{A}_i}(\tilde{x}_i)$, i.e., as a set in which the values of the mode parameters have the maximum values of the membership function.

11. Based on expression (3), the numerical values of the output parameters of the object y_j^d are determined as the argument of the maximum membership value, i.e., according to the formula:

$$y_j^M = \underset{\tilde{y}_j^d}{\mathrm{argmax}}\left(\tilde{y}_j^*\right). \tag{4}$$

To check the adequacy of the synthesized linguistic model, go to point 14.

12. Fuzzy models are synthesized for an object with crisp input and fuzzy output parameters. The structure of fuzzy models based on the idea of the method of sequential inclusion of regressors can be identified as:

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{n_1} \tilde{a}_{ij} x_{ij} + \sum_{i=1}^{n_1} \sum_{k=i}^{n_1} \tilde{a}_{ikj} x_{ij} x_{kj} + \ldots,\ i = 1, \ldots, n_1,\ j = m_1 + 1, \ldots, m, \tag{5}$$

where $\tilde{a}_{0j}$, $\tilde{a}_{ikj}$—unknown fuzzy parameters (regression coefficients) that need to be identified. The first sum constitutes the linear part of the fuzzy models, the subsequent sums constitute the nonlinear part.

13. Fuzzy parameters of models (5) are identified. The following approach to identifying fuzzy parameters is proposed. Fuzzy models based on the α-level set are transformed into a set of crisp models:

$$y_j^{\alpha_l} = a_{0j}^{\alpha_l} + \sum_{i=1}^{n_1} a_{ij}^{\alpha_l} x_{ij} + \sum_{i=1}^{n_1} \sum_{k=i}^{n_1} a_{ikj}^{\alpha_l} x_{ij} x_{kj},\ l = 1, \ldots L. \tag{6}$$

where $\alpha_l, = 1, \ldots L$—α-level set; l—index of α-level set; L—number of α-level set.

Then, the unknown values of the parameters $a_{0j}^{\alpha_l}, a_{ij}^{\alpha_l},\ a_{ikj}^{\alpha_l}$ of the obtained crisp models can be identified using known methods of parametric identification. After identifying the parameters of model (6) at α-levels, for example, based on the least square method, the obtained values of the parameters must be combined according to the formula [18]:

$$\tilde{a}_{ij} = \bigcup_{\alpha\in[0,5\div 1]} a_{ij}^{\alpha_l} \text{or} \mu_{\tilde{a}_{ij}}(a_{ij}) = \sup_{\alpha\in[0,5\div 1]} \min\left\{\alpha_l, \mu_{a_{ij}}^{\alpha_l}(a_{ij})\right\}, \quad (7)$$

where $a_{ij}^{\alpha_l} = \left\{\tilde{a}_{ij}|\mu_{\tilde{a}_{ij}}(a_{ij})| \geq \alpha\right\}$.

14. The adequacy of the developed models is checked. In this case, the following can be chosen as adequacy criteria:

$$R = \min\sum_{j=1}^{m}\left(y_j^M - y_j^E\right)^2 \leq R_D,$$

where y_j^M and y_j^E, respectively, represent the models calculated according to other models that are real and obtained, for example, experimentally at the object, the values of the output parameters; R_D—permissible deviation between y_j^M and y_j^R.

15. If the condition of adequacy of the models is met, then the obtained models are recommended for practical application in the optimization and control of the operating modes of the modeled object. Otherwise, the reasons for the inadequacy of the developed models are determined and the transition is carried out back to the corresponding points of the method to eliminate them and ensure the adequacy of the developed models.

3. Results

3.1. Hybrid Models of Atmospheric Block Columns of Primary Oil Refining Unit Based on Available Experimental-Statistical and Fuzzy Information

Based on the proposed in Section 2 hybrid method for developing a set of statistical, fuzzy and linguistic models of complex objects in conditions of shortage and fuzziness of the initial information, we synthesize models C-1 and C-2 of the atmospheric block of the primary oil refining unit. In accordance with paragraph four of the proposed method, the following structure of the statistical model of column C-1 was identified, determining the yield of gasoline of the 180 °C fraction and stripped oil fed to C-2:

$$y_j = a_{0j} + \sum_{i=1}^{3} a_{ij}x_i + \sum_{i=1}^{3}\sum_{k=i}^{3} a_{ikj}x_i x_k, \quad j = 1, 2, \quad (8)$$

where y_1—volume of gasoline of 180 °C fraction supplied to the stabilization column; y_2—volume of stripped oil supplied to C-2; $x_i,\ i = \overline{1,3}$—input, operating parameters C-1; x_1—volume of feedstock (desalted oil); x_2—temperature in C-1; x_3—pressure in C-1.

After identifying the unknown parameters of the models (8) based on an array of experimental statistical data using the REGRESS software package 3.1, in which the least squares method is implemented programmatically, the following models for determining the volume of product yield from C-1 were obtained:

$$\begin{gathered} y_1 = 11.1 + 0.008615385x_1 + 0.029473684x_2 - 1.555555556x_3 + 0.000026509x_1^2 \\ +0.000077562x_2^2 + 0.864197531x_3^2, \end{gathered} \quad (9)$$

$$\begin{gathered} y_2 = 118.7 + 0.091384615x_1 + 0.312631579x_2 - 16.500000000x_3 + 0.000281183x_1^2 \\ +0.000822715x_2^2 + 9.166666667x_3^2. \end{gathered} \quad (10)$$

In accordance with paragraph 12 of the proposed system method, in Section 2, the following structure of a fuzzy model is identified that estimates the end boiling point of the gasoline of the fraction "not higher", i.e., $\tilde{<}$ 180 °C:

$$\tilde{y}_3 = \tilde{a}_0 + \tilde{a}_1 x_2 + \tilde{a}_2 x_3 + \tilde{a}_3 x_2^2 + \tilde{a}_4 x_3^2. \tag{11}$$

Then, the fuzzy model (11) according to Formula (6) is presented as a set of crisp models at a set of levels α = {0.5;0.8;1}. Since the Gaussian membership functions constructed using the Fuzzy Logic Toolbox toolkit of the MATLAB system R2018b are symmetrical, five crisp regression-type models were obtained at the levels α = {0.5;0.8;1;0.8;0.5}. Based on the REGRESS software package 3.1, the parameters were identified, i.e., the regression coefficients of the obtained crisp models at α-levels, which, due to their large volume, are given in Appendix A.

After combining the identified parameters at α-levels using Formula (7), the following model was obtained, suitable for determining the end of boiling point of gasoline:

$$\tilde{y}_3 = 18 + 0.284210526x_2 + 30.00x_3 + 0.000997x_2^2 + 5.55x_3^2 \tilde{<} 180\ ^\circ\text{C}. \tag{12}$$

The product (stripped oil) from the bottom of column C-1 is heated in furnace F-2 to the required temperature (360–385 °C) and fed to the rectification column C-2 for separation into other gasoline fractions and fuel oil. The developed models of column C-2 based on the method proposed in Section 2, determining the volumes of gasoline fractions 180–220, 220–280, and 280–350 °C, fuel oil fraction < 350 °C have the following structures:

$$y_j = a_{0j} + \sum_{i=4}^{6} a_{ij} x_i + \sum_{i=4}^{6} \sum_{k=i}^{6} a_{ikj} x_i x_k, \quad j = \overline{4,7}, \tag{13}$$

where y_4—volume of gasoline fractions 180–220 °C; y_5—volume of gasoline fractions 220–280 °C; y_6—volume of kerosene-gas oil fractions 280–350 °C; y_7—volume of fuel oil of the <350 °C fraction; x_i, $i = \overline{4,6}$—input, operating parameters C-2:x_4—volume of feedstock (partially stripped oil from C-1); x_5—temperature in C-2; x_6—pressure in C-2.

After identifying the unknown parameters of the models (13) in the manner described above using the REGRESS software package 3.1, the following models for determining the volume of product output from C-2 were obtained depending on its input and operating parameters:

$$y_4 = 11.2 + 0.00471381x_4 + 0.02709677x_5 - 1.4x_6 + 0.00003174x_4^2 + 0.000029136x_5^2 + 0.35x_6^2, \tag{14}$$

$$y_5 = 36 + 0.016835017x_4 + 0.0967741945 - 3.0x_6 + 0.000113367x_4^2 + 0.000104058x_5^2 + 1.25x_6^2, \tag{15}$$

$$y_6 = 4 + 0.001683502x_4 + 0.009677419x_5 - 0.5x_6 + 0.000011337x_4^2 + 0.000010406x_5^2 + 0.125x_6^2, \tag{16}$$

$$y_7 = 48 + 0.025252525x_4 + 0.145161290x_5 + 1.5x_6 + 0.000170051x_4^2 + 0.000156087x_5^2 + 1.875x_6^2. \tag{17}$$

In accordance with paragraph 12 of the proposed method in Section 2, the following structure of fuzzy models is identified, allowing to evaluate the quality of gasoline fractions and fuel oil from C-2:

$$\tilde{y}_j = \tilde{a}_0 + \tilde{a}_1 x_5 + \tilde{a}_2 x_6 + \tilde{a}_3 x_5^2 + \tilde{a}_4 x_5 x_6 + \tilde{a}_5 x_6^2 \tilde{<} b_j,\ j = \overline{8,11}, \tag{18}$$

where $\tilde{y}_8, \tilde{y}_9, \tilde{y}_{10}$, and $\tilde{y}_{11}$ respectively represent gasoline fractions with boiling ends $b_8 \tilde{\leq} 200$, $b_9 \tilde{\leq} 280$, $b_{10} \tilde{\leq} 350$ °C, and fuel oil fractions with the beginning of boiling $b_{11} \tilde{\geq} 350$ °C.

Then, similarly to the fuzzy model (11), model (18), shown in Formula (6), is represented by a set of crisp models on a set of levels α = {0.5;0.8;1} and, using the REGRESS software package, the regression coefficients of the obtained crisp models on α-levels are identified. For example, the results of parametric identification of the quality of gasoline fraction 180–220 °C $\widetilde{y}_8$ on sets of α-level yielded the following parameters of model (19), given in Appendix B. The parameters of the remaining fuzzy models, assessing the quality of other gasoline fractions and fuel oil, were identified in a similar manner.

After combining the identified parameters at the α-levels using Formula (7), the following models were obtained for determining the end boiling point of the gasoline fraction from column C-2:

$$\widetilde{y}_8 = 100.0 + 0.153846154x_5 + 30.00x_6 + 0.001183432x_5^2 \,\widetilde{<}\, 200, \tag{19}$$

$$\widetilde{y}_9 = 137.50 + 0.110x_5 + 41.250x_6 + 0.000440x_5^2 \,\widetilde{<}\, 280. \tag{20}$$

$$\widetilde{y}_{10} = 175 + 0.102941176x_5 + 52.50x_6 + 0.000302768x_5^2 \,\widetilde{<}\, 350, \tag{21}$$

$$\widetilde{y}_{11} = 175.0 + 0.106060606x_5 + 52.50x_6 + 0.000321396x_5^2 \,\widetilde{>}\, 350. \tag{22}$$

In the above-obtained models of columns C-1 and C-2 of the atmospheric block of the primary oil refining unit (9)–(12), (14)–(17), and (19)–(22), the regressors that have zero coefficients, i.e., those not affecting the output parameters, are neglected and are not given in the indicated models.

3.2. Linguistic Models for Assessing the Quality of Gasoline from the Atmospheric Block Outlet

The following basic fuzzy requirement is imposed on gasolines from the atmospheric block outlet according to the internal standard CT TOO 40319154-13-2018 of Atyrau Refinery: end boiling point "not higher than 205 °C". To take this fuzzy requirement into account, in accordance with paragraphs 5–11 of the proposed method, linguistic models have been developed making it possible to assess the quality of gasoline from the atmospheric block outlet ($\widetilde{y}_{12}$) depending on the fuzzy values of the content of chloride salts in desalted oil ($\widetilde{x}_7$) and the mass fraction of sulfur in the feedstock ($\widetilde{x}_8$) of the atmospheric block. The values of the input and output linguistic variables are determined with the involvement of DM and experts. The Fuzzy Logic Toolbox application of the MATLAB system R2018b is used to construct the membership function and fuzzy modeling [45,46].

The selected fuzzy input and output parameters of the atmospheric block are described by the term sets: $\widetilde{x}_7$ = {"low", "below average", "average", "above average", "high"}; $\widetilde{x}_8$ = {"low", "below normal", "normal", "above normal", "high"}; $\widetilde{y}_{12}$ = {"very low", "low", "average", "high", "very high"} (item 7 of the proposed method).

Table 1 shows the abbreviated notations of the selected terms used in fuzzification, i.e., constructing the membership function of the parameters $\widetilde{x}_7$, $\widetilde{x}_8$, and $\widetilde{y}_{12}$.

Table 1. Abbreviated notations of input and output linguistic variable terms for fuzzification of rule base formation.

Terms of Fuzzy Parameters	Symbol
Low	*LW*
Below average	*BA*
Average	*AR*
Above average	*AA*

Table 1. *Cont.*

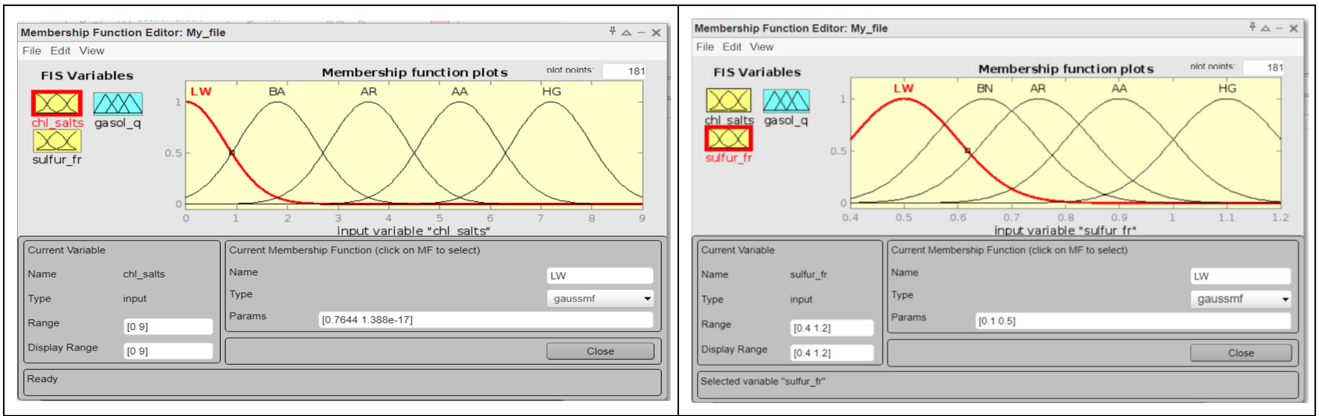
Terms of Fuzzy Parameters	Symbol
High	*HG*
Below normal	*BN*
Normal	*NR*
Above normal	*AN*
Very low	*VLW*
Very high	*VHG*

The universes of the given linguistic variables required for constructing the membership function are given in Table 2.

Table 2. The universes for fuzzy parameters $\tilde{x}_7$, $\tilde{x}_8$, and $\tilde{y}_{12}$.

Fuzzy Input Parameters	Values of Fuzzy Input Variables				
	LW	***BA, BN***	***AR, NR***	***AA, AN***	***HG***
$\tilde{x}_7$ —content of chloride salts in the feedstock of the AT block	0–1	1–3	3–5	5–7	7–9
$\tilde{x}_8$ —mass fraction of sulfur in the feedstock of the AT block	0.4–0.6	0.6–0.7	0.7–0.8	0.8–1.0	1.0–1.2
Fuzzy Output Parameter	**Fuzzy Output Parameter Values**				
	VLW	***LW***	***AR***	***HG***	***VHG***
$\tilde{y}_{12}$—quality of gasoline from the outlet of the AT unit	190–196	196–202	202–208	208–214	214–220

The fuzzification procedures and other procedures of the fuzzy inference algorithm are implemented in the Fuzzy Logic Toolbox. Figure 3a,b shows the Gaussian-type membership functions for the fuzzy input parameters $\tilde{x}_7$, $\tilde{x}_8$.



(**a**) (**b**)

Figure 3. Membership functions of fuzzy input parameters: (**a**) $\tilde{x}_7$—content of chloride salts (chl_salts) in the feedstock of the AT block; (**b**) $\tilde{x}_8$—mass fraction of sulfur (sulfur_fr) in the feedstock of the AT block.

In Figure 4, the membership functions of the output parameter $\tilde{y}_{12}$ are constructed using the Fuzzy Logic Toolbox.

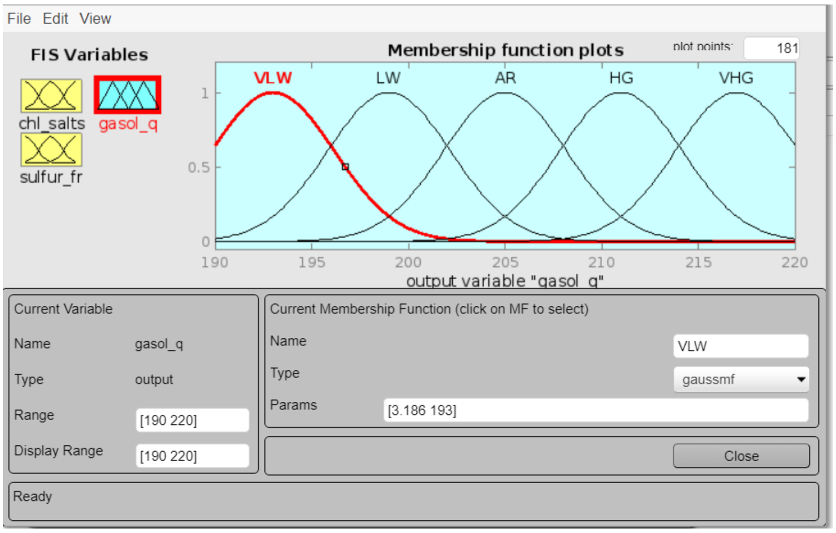


Figure 4. Membership functions of the output parameter $\tilde{y}_{12}$—gasoline quality (gasoil_q) (end of boiling) from the outlet of the AT block.

The developed linguistic models for the fuzzy inference system, which allow us to estimate the quality of the gasoline from the outlet of the atmospheric block $(\tilde{y}_{12})$, are presented below in the form of fuzzy production rules.

$$\begin{array}{l}
Rule\ 1: \ IF\ «\tilde{x}_7\ is\ LW»\ and\ «\tilde{x}_8\ is\ LW»\ THEN\ «\tilde{y}_{12}\ is\ VLW»\ F_1; \\
Rule\ 2: \ IF\ «\tilde{x}_7\ is\ LW»\ and\ «\tilde{x}_8\ is\ BN»\ THEN\ «\tilde{y}_{12}\ is\ VLW»\ F_2; \\
Rule\ 3: \ IF\ «\tilde{x}_7\ is\ BA»\ and\ «\tilde{x}_8\ is\ LW»\ THEN\ «\tilde{y}_{12}\ is\ VLW»\ F_3; \\
Rule\ 4: \ IF\ «\tilde{x}_2\ is\ BA»\ and\ «\tilde{x}_8\ is\ BN»\ THEN\ «\tilde{y}_{12}\ is\ VLW»\ F_4; \\
Rule\ 5: \ IF\ «\tilde{x}_7\ is\ LW»\ and\ «\tilde{x}_8\ is\ NR»\ THEN\ «\tilde{y}_{12}\ is\ VLW»\ F_5; \\
Rule\ 6: \ IF\ «\tilde{x}_7\ is\ AR»\ and\ «\tilde{x}_8\ is\ LW»\ THEN\ «\tilde{y}_{12}\ is\ LW»\ F_6; \\
Rule\ 7: \ IF\ «\tilde{x}_7\ is\ BA»\ and\ «\tilde{x}_8\ is\ NR»\ THEN\ «\tilde{y}_{12}\ is\ LW»\ F_7; \\
Rule\ 8: \ IF\ «\tilde{x}_7\ is\ AR»\ and\ «\tilde{x}_8\ is\ BN»\ THEN\ «\tilde{y}_{12}\ is\ LW»\ F_8; \\
Rule\ 9: \ IF\ «\tilde{x}_7\ is\ AR»\ and\ «\tilde{x}_8\ is\ NR»\ THEN\ «\tilde{y}_{12}\ is\ LW»\ F_9; \\
Rule\ 10: \ IF\ «\tilde{x}_7\ is\ LW»\ and\ «\tilde{x}_8\ is\ AA»\ THEN\ «\tilde{y}_{12}\ is\ LW»\ F_{10}; \\
Rule\ 11: \ IF\ «\tilde{x}_7\ is\ AA»\ and\ «\tilde{x}_8\ is\ LW»\ THEN\ «\tilde{y}_{12}\ is\ AR»\ F_{11}; \\
Rule\ 12: \ IF\ «\tilde{x}_7\ is\ BA»\ and\ «\tilde{x}_8\ is\ AA»\ THEN\ «\tilde{y}_{12}\ is\ AR»\ F_{12}; \\
Rule\ 13: \ IF\ «\tilde{x}_7\ is\ AA»\ and\ «\tilde{x}_8\ is\ BN»\ THEN\ «\tilde{y}_{12}\ is\ AR»\ F_{13}; \\
Rule\ 14: \ IF\ «\tilde{x}_7\ is\ AR»\ and\ «\tilde{x}_8\ is\ AA»\ THEN\ «\tilde{y}_{12}\ is\ AR»\ F_{14}; \\
Rule\ 15: \ IF\ «\tilde{x}_7\ is\ AA»\ and\ «\tilde{x}_8\ is\ NR»\ THEN\ «\tilde{y}_{12}\ is\ AR»\ F_{15}; \\
Rule\ 16: \ IF\ «\tilde{x}_7\ is\ AA»\ and\ «\tilde{x}_8\ is\ AA»\ THEN\ «\tilde{y}_{12}\ is\ HG»\ F_{16}; \\
Rule\ 17: \ IF\ «\tilde{x}_7\ is\ LW»\ and\ «\tilde{x}_8\ is\ HG»\ THEN\ «\tilde{y}_{12}\ is\ HG»\ F_{17}; \\
Rule\ 18: \ IF\ «\tilde{x}_7\ is\ HG»\ and\ «\tilde{x}_8\ is\ LW»\ THEN\ «\tilde{y}_{12}\ is\ HG»\ F_{18}; \\
Rule\ 19: \ IF\ «\tilde{x}_7\ is\ BA»\ and\ «\tilde{x}_8\ is\ HG»\ THEN\ «\tilde{y}_{12}\ is\ HG»\ F_{19}; \\
Rule\ 20: \ IF\ «\tilde{x}_7\ is\ HG»\ and\ «\tilde{x}_8\ is\ BN»\ THEN\ «\tilde{y}_{12}\ is\ HG»\ F_{20}; \\
Rule\ 21: \ IF\ «\tilde{x}_7\ is\ AR»\ and\ «\tilde{x}_8\ is\ HG»\ THEN\ «\tilde{y}_{12}\ is\ VHG»\ F_{21}; \\
Rule\ 22: \ IF\ «\tilde{x}_7\ is\ HG»\ and\ «\tilde{x}_8\ is\ NR»\ THEN\ «\tilde{y}_{12}\ is\ VHG»\ F_{22}; \\
Rule\ 23: \ IF\ «\tilde{x}_7\ is\ AA»\ and\ «\tilde{x}_8\ is\ HG»\ THEN\ «\tilde{y}_{12}\ is\ VHG»\ F_{23}; \\
Rule\ 24: \ IF\ «\tilde{x}_7\ is\ HG»\ and\ «\tilde{x}_8\ is\ AA»\ THEN\ «\tilde{y}_{12}\ is\ VHG»\ F_{24}; \\
Rule\ 25: \ IF\ «\tilde{x}_7\ is\ HG»\ and\ «\tilde{x}_8\ is\ HG»\ THEN\ «\tilde{y}_{12}\ is\ VHG»\ F_{25};
\end{array} \tag{23}$$

$F_1,\ldots,F_{25}$—weighting coefficients reflecting the degree of confidence in the truth of sub-conclusions in the calculated rule base are taken to be equal to 1. For different values of the degrees of confidence, they can take values from 0 to 1.

Then, the compiled rule base, which is a fuzzy knowledge base, is implemented using the Fuzzy Logic Toolbox and is presented in Figure 5.

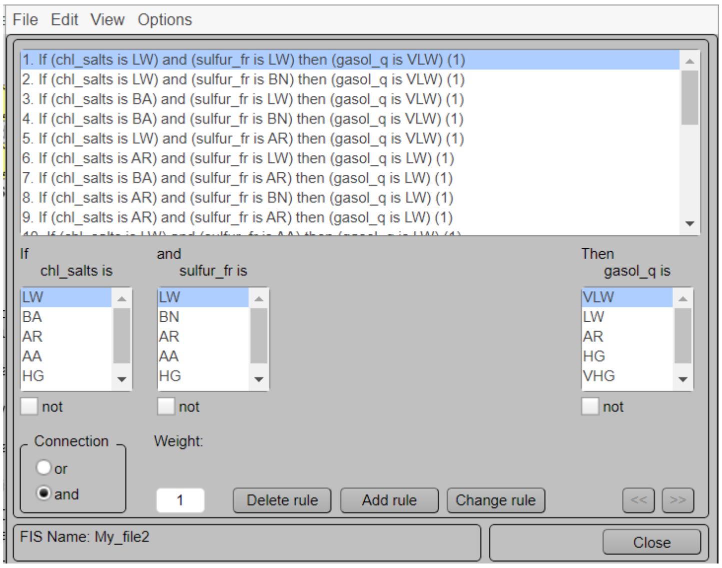


Figure 5. Fuzzy knowledge base for input and output parameters.

The fuzzy modeling results after visualization in the RuleViewer are shown in Figure 6.

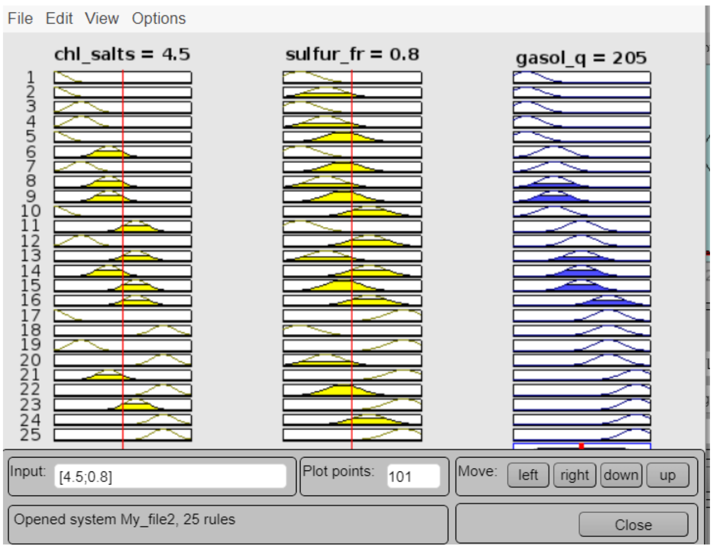


Figure 6. Results of visualization of fuzzy logical inference in the RuleViewer.

In the Surface Viewer, the "inlet-outlet" surface corresponding to the compiled fuzzy system is shown in Figure 7. The provided surface allows the results of fuzzy modeling to be viewed and analyzed, determining the best values for the quality of the gasoline of the AT block depending on its fuzzy input parameters.

The results of modeling the process of primary oil refining, taking place in an atmospheric column, based on the systems of statistical, fuzzy, and linguistic models (9)–(12) (14)–(23) developed by us and known models developed using traditional methods, are compared. The results of modeling based on developed and known models for ease of analysis and comparison are included in Table 3.

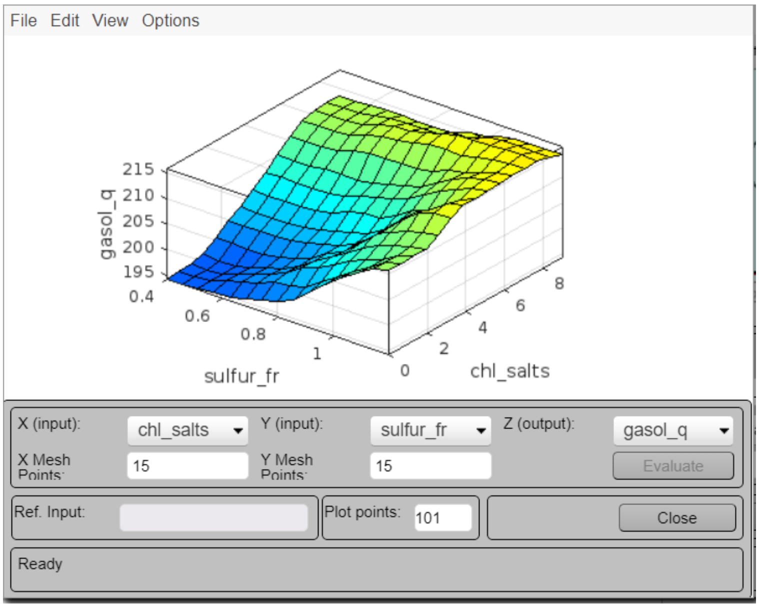


Figure 7. "Inlet-outlet" surface in SurfaceViewer.

Table 3. Results of modeling the process of primary oil refining with known models [47] and the developed system of different models using additional fuzzy information and experimental real data from the AT unit of Atyrau refinery.

Volumes and Quality Indicators of Products	**Known Models [47]**	**Developed Model Systems**	**Real Experimental Data**
Volume of gasoline fraction 180 °C from column C-1, y_1;	27.2	28.7	28
Volume of stripped oil from column C-1, y_2;	299	297	297
Quality of gasoline fraction 180 °C, $\widetilde{y}_3$;	–	175	$(178)^L$
Volume of gasoline fraction 180–220 °C from column C-2, y_4;	27.2	28.3	27.8
Volume of gasoline fraction 220–280 °C from column C-2, y_5;	100	100	100
Volume of gasoline fraction 280–350 °C from column C-2, y_6;	10.3	10	10
Volume of fuel oil with initial boiling point <350 °C from column C-2, y_7;	151	149.5	150
Quality of gasoline fraction 180–220 °C, $\widetilde{y}_8$;	–	200.3	$(210)^L$
Quality of gasoline fraction 220–280 °C, $\widetilde{y}_9$;	–	275	$(278)^L$
Quality of gasoline fraction 280–350 °C, $\widetilde{y}_{10}$;	–	347	$(350)^L$
Fuel oil quality with initial boiling point <350 °C, $\widetilde{y}_{11}$;	–	358	$(360)^L$
Quality of gasoline from the outlet of the AT block, $\widetilde{y}_{12}$;	–	200	$(200)^L$
Values of input and operating parameters of the AT block			
x_1^*—volume of the feedstock in C-1 (desalted oil);	325.7	325.7	325.7
x_2^*—temperature in C-1;	193	190	190
x_3^*—pressure in C-1;	1.85	1.80	1.80
x_4^*—volume of the feedstock in C-2;	297	297	297
x_5^*—temperature in C-2;	312	310	311
x_6^*—pressure in C-2;	2.10	2	2
x_7^*—content of chloride salts in the feedstock of the AT block;	–	4	$(4)^L$
x_8^*—mass fraction of sulfur in the feedstock of the AT block;	–	0.75	$(0.75)^L$

Note: – means that these parameters are not determined by this method; $(\cdot)^L$—these parameters are not measured directly: they are estimated in the laboratory with human participation.

From the analysis of the obtained results of modeling based on the developed models of the atmospheric block, given what is presented in Table 3, it can be concluded that the improvement of the developed models of the main, interconnected columns C-1 and C-2 of the atmospheric block under study is statistically significant enough. The justification for this conclusion is:

- the volumes of gasoline produced from the outlet of columns C-1 and C-2, determined on the basis of modeling and optimization, have been increased by 1.5 and 1.1 tons/day, respectively, or by more than 5%, which allows for significant additional profits to be obtained monthly. This is achieved by increasing more valuable oil products (gasolines) at the expense of a slight decrease in less valuable and not particularly in-demand oil products (heavy fractions, fuel oil);
- the developed models, due to the additional use of fuzzy information, determine and improve the quality characteristics of the target products of the atmospheric block—gasolines of different fractions. The compared known models do not allow the user to evaluate these described fuzzy quality indicators of gasoline;
- the values of input and mode parameters that provide the best values of output parameters and models $\left(x_1^*,\ x_2^*,\ x_3^*,\ x_4^*,\ x_5^*\right)$ show that the proposed method is more energy efficient compared to known models. This is evident from the simulation results (Table 3), since the developed models provide better results compared to known models, at lower values of temperature and pressure, i.e., they require less energy.

In this study, also based on the modified method of sequential inclusion of regressors, the structure of mathematical models of the studied atmospheric column C-2 was identified, describing the dependence of gasoline (y_1), kerosene (y_2), and fuel oil (y_3) from its output on the input and operating parameters (x_1,x_2, x_3):

$$y_j = a_{0j} + \sum_{i=1}^{3} a_{ij} x_i + \sum_{i=1}^{3}\sum_{k=i}^{3} a_{ikj} x_i x_k, \quad j = 1,3, \tag{24}$$

where $y_j,\ j = \overline{1,3}$—volumes, respectively: gasoline; kerosene and fuel oil from column C-2; $x_i,\ i = \overline{1,3}$—input, operating parameters of C-2, respectively: volume of feedstock; pressure and temperature in C-2; a_{0j}, a_{ij} and a_{ikj}—unknown parameters (regression coefficients) of the model (24), identified on the basis of statistical data and the MATLAB package.

The collected statistical data: the values of the input and operating parameters and the corresponding values of the output parameter (gasoline), as well as the identified regression coefficients and predicted values of y_1, obtained using model (24), are presented in Table 4.

Table 4. Daily values of input and output data and results of parametric identification of the model for determining gasoline from the atmospheric column C-2 and the result of the predicted model.

Input and Operating Parameters				Output Parameter, Its Value Obtained using the Model and Regression Coefficients		
№	x_1, Feedstock	x_2, Pressure	x_3, Temperature	Gasoline from C2	y1,_predicted	Regression Coefficients
1	28	1.05	151	22	22.7152185843006	0
2	26	1.07	152	32	34.3678126088635	0
3	25	1.06	153	33	33.1812361561751	0
4	26	1.03	153	25	32.0912636236317	0
5	25	1.07	153	22	26.8781283098942	0
6	26	1.06	153	29	28.3653979109658	0

Table 4. *Cont.*

Input and Operating Parameters				Output Parameter, Its Value Obtained using the Model and Regression Coefficients		
№	x_1, Feedstock	x_2, Pressure	x_3, Temperature	Gasoline from C2	y_1,_predicted	Regression Coefficients
7	28	1.02	153	34	30.5778940470773	−3.06266442343409
8	29	1.01	153	31	34.3451825095981	−3486.86945250334
9	26	1.02	153	28	33.3179949048208	23.9985109074938
10	29	1.04	153	23	28.2582532063534	445.100000656846
11	27	1.03	153	31	34.4388347226777	−0.00591801193267827
12	26	1.05	153	30	32.2750694541901	46427.6363118354
13	25	1.04	153	32	31.1726986094291	−0.00725317030931101
14	27	1.07	153	29	31.3957169282658	12.5955616123985
15	24	1.04	153	30	29.4863686395547	−0.0799576916252932
16	28	1.04	152	34	27.5468888687465	−1175.21240063277
17	30	1.02	153	41	33.2809373404161	1375.32016596489
18	29	0.98	153	40	39.2199700925266	6.96191204520193
19	33	0.98	153	35	35.6346020880301	−0.0668990967460236
20	28	1	153	27	26.5841881011293	0
21	32	1.01	153	34	34.1134642006655	0
22	33	1.01	153	25	25.6305230872676	0
23	23	1.02	153	23	28.3640467413643	0
24	24	1.01	153	28	30.7583092534769	0

Based on the data in Table 1, the final form of the model for determining the gasoline yield depending on the input and operating parameters can be written as:

$$\begin{aligned} y_1 = & -3.06x_2^2 - 3486.86x_3^2 + 23.99x_1x_2 + 445.1x_1x_3 - 0.005x_2x_3 + 46427.63x_1^3 - 0.0073x_2^3 + 12.59x_3^3 \\ & -0.079x_1^2x_2 - 1175.21x_1^2x_3 + +1375.32x_2^2x_3 + 6.96x_1x_2^2 - 0.067x_2x_3^2. \end{aligned} \quad (25)$$

Figure 8 shows graphs for comparing real and model data on gasoline yield, and Figure 9 shows graphs of the dependence of the volume of gasoline from the atmospheric column C-2 on the feedstock (volume of gasoline from C-1) and the pressure in C-2.

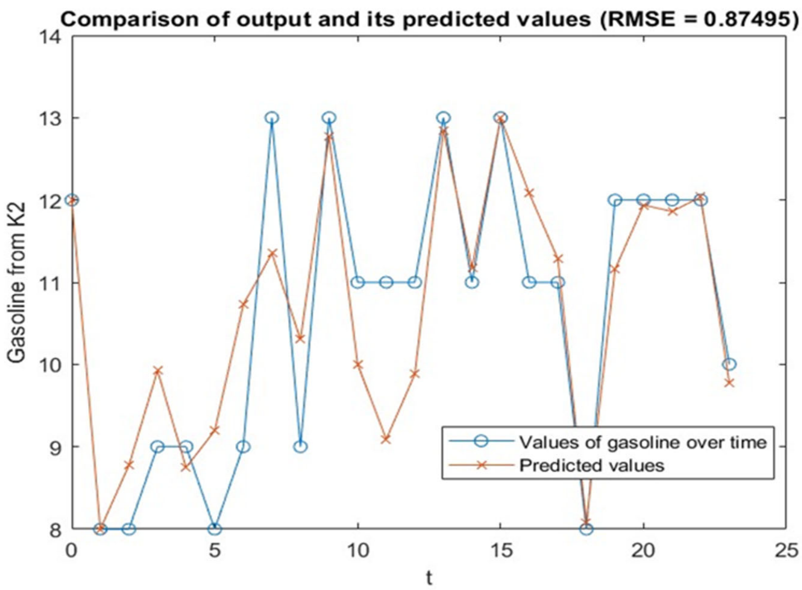


Figure 8. Comparison of actual gasoline data and their predicted values.

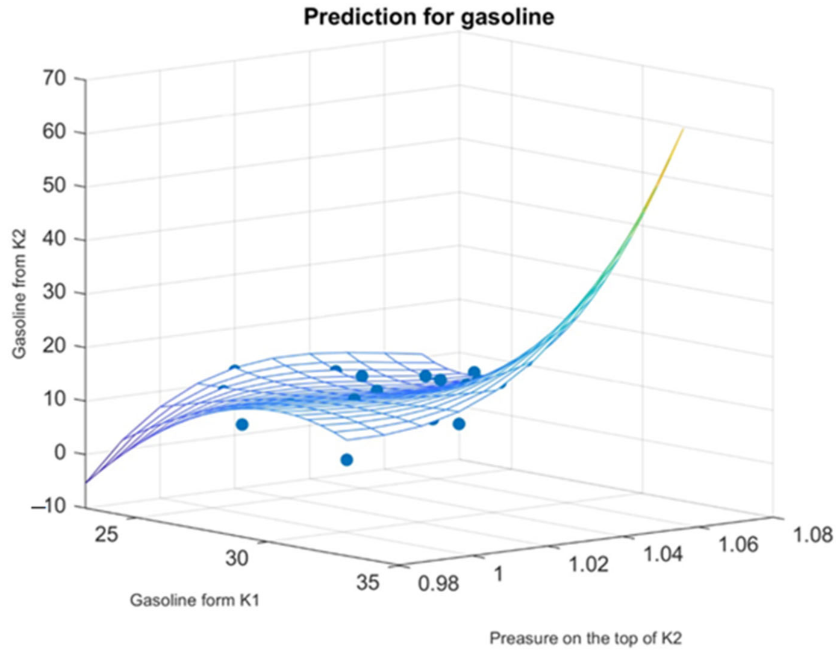


Figure 9. Dependence of the volume of gasoline at the outlet of the atmospheric column C-2 on the volume of gasoline at the outlet of C-1 and the pressure in C-2.

4. Discussion of Results

In the developed hybrid models of C-1 and C-2 atmospheric block columns of the primary oil refining unit, the input, operating parameters, and volume of oil products at their outlet are crisp. Therefore, to determine the volume of oil products from the outlet of the atmospheric block using the proposed system method, statistical nonlinear models of the polynomial type (9)–(10), (14)–(17) are developed. The structure and parameters of these models are identified based on the method of sequential inclusion of regressors and experimental statistical data using the REGRESS software package, which implements the least squares method. Fuzzy models (12), (19)–(22) are developed to determine the fuzzy estimated quality indicators of gasoline fractions and fuel oil from the atmospheric block. The structure of these fuzzy models is identified based on a modification of the method of sequential inclusion of regressors. Moreover, fuzzy parameters are identified by transforming fuzzy models into sets of crisp models based on a set of α-level of fuzzy set theory using Formula (6) of the proposed system method. Then, using experimental statistical data and the REGRESS software package, the values of the parameters on the sets of α-level are obtained. After that, combining the values of the parameters identified on the sets of α-level using Formula (7), the parameters of models (12) and (19)–(22) are determined.

The right part of Table 2 shows the names of the input parameters: the content of chloride salts $\widetilde{x}_7$ and the mass fraction of sulfur $\widetilde{x}_8$ in the raw materials of the AT unit, which, in practice, are fuzzy and estimated with the participation of the experts of the primary oil refining unit, the central plant laboratory. The lower part of the first column of the table shows the fuzzy output parameter $\widetilde{y}_{12}$—the end of boiling gasoline from the output of the atmospheric block, which also estimates the quality of gasoline from the output of the AT block. And, in the left part of this table, the intervals of numerical values and fuzzy terms, estimating fuzzy input and output parameters, are given.

In Figure 3, the Gaussian-type functions (gaussmf) of the Fuzzy Logic Toolbox application are selected for the membership function of fuzzy described parameters. This is justified by the fact that such a nonlinear dependence of the Gaussian type allows one to more adequately form an opinion about the membership of a fuzzy parameter to the corresponding terms that describe its parameter.

The constructed linguistic models of the atmospheric block of the primary oil refining unit using the proposed method of synthesizing linguistic models allow fuzzy modeling of the gasoline production process in the Fuzzy Logic Toolbox, and selecting the optimal operating mode of the atmospheric block. As can be seen from the results of fuzzy modeling, from the inlet–outlet surface in the SurfaceViwer (Figure 7): the lower the content of chloride salts and the mass fraction of sulfur in the feedstock of the AT block, the lower the boiling point of gasoline, i.e., the quality of gasoline improves, and vice versa. This corresponds to the developed rule base and means that it is necessary to choose a compromise solution when choosing the values of the input parameters of the atmospheric block. This is due to the fact that, on the one hand, an increase in output parameters allows increasing the volume of gasoline; however, on the other hand, it worsens its quality. To do this, it is necessary to solve the problem of making decisions on choosing the best compromise solution.

The results of the visualization of fuzzy inference in Rule Viewer (Figure 6) allow us to review the rules for the fuzzy inference of each rule, the resulting fuzzy set, and the implementation of the defuzzification procedure. This figure shows the results of modeling in the case when the input parameters are entered: the content of chloride salts in the feedstock is 4.5% and the mass fraction of sulfur in the feedstock is 0.8%. Then, as a result of fuzzy modeling, the volatility, i.e., the quality (end of boiling) of gasoline is equal to 205 °C. This means that the quality of gasoline is average (see Table 2). Using the developed fuzzy inference system, by changing the values of the input parameters of the atmospheric block, i.e., by simulating its operating modes, it is possible to evaluate and select the best value of gasoline quality taking into account the required volume.

The analysis of the improved output data obtained based on the proposed output data methods: volume and quality of gasoline from the atmospheric unit, as can be seen from the results given in Table 3, shows their practical significance, since:

- compared to the projections of known models, the results obtained on the basis of the hybrid model are improved and more accurately coincide with the actual operational data obtained at the research site. At the same time, the improvement of the output data consists of increasing the volume of the target, more in-demand gasolines on the market (fractions up to 280 °C) by an average of 5%, which allows for a significant economic effect;
- as can be seen from Table 3, the developed fuzzy and linguistic models allow for determining the quality indicators of the target gasoline produced in the atmospheric block, which are characterized by fuzziness and are not determined by known methods. In practice, these quality indicators are approximately determined with the participation of specialists, and laboratory assistants in laboratory conditions based on their knowledge and experience. As a result, a comparison of the gasoline quality indicators determined in laboratory conditions, which are determined after several days, promptly determined indicators based on the proposed models coincide with the actual data and are more improved;
- the accuracy of the forecasts of the developed hybrid model is effectively reflected in the actual operation of oil refineries and allows obtaining additional profit due to the increase in the output of higher quality and marketable gasoline fractions. From Table 3, it is clear that the developed hybrid model of the atmospheric block allows for improving the volume and quality of the target gasoline at lower costs for ensuring the required values of temperature and pressure than the compared known models. This allows for a reduction in energy costs for increasing temperature and pressure, i.e., the proposed approach is more energy efficient.

The method of gradual formalization of decision-making models proposed by Volkova in [48] is a contribution to the development of modern methods of system analysis. When developing and improving models of the atmospheric block of the primary oil refining unit, the use of this method of gradual formalization of decision-making models allows improvements in the quality of the developed models. In future studies, the authors plan to improve the quality and the developed models and optimize oil-refining objects based on the method of gradual formalization of decision-making models.

Due to the deterioration of the environmental situation in the contaminated area of oil refineries, there is a significant deterioration of the environment. Emissions of harmful gases, waste, and by-products of oil refineries are a dangerous source of pollution. In addition to affecting air quality, they can also pollute soil and water, thereby damaging ecosystems and causing serious environmental problems. At the same time, oil and oil product pollution is found everywhere: in the soil layer, hydrosphere, atmosphere, they, entering into the environment, cause it significant environmental damage. Therefore, in the processes of oil refining, reducing the environmental load on the environment and increasing environmental safety is one of the important and urgent issues. During primary processing, in addition to emissions of CO_2, hydrogen sulfide-containing gases, sulfur dioxide and other harmful gases, other factors such as waste, used refrigerants, dirty water, soot, solid waste from oil refining, and resource consumption also have a negative impact on the environment.

The results obtained in this study facilitate an increase in the volumes of higher - quality "clean" gasoline fractions and reduce the volumes of low-quality "dirty" gasoline fractions, and also reduce energy consumption, thereby reducing the environmental impact of primary oil refining processes on the environment.

Analysis and comparison of the modeling results of the atmospheric block operation based on known models and the developed system of various models using additional fuzzy information given in Table 3 allows us to highlight the following advantages of the proposed modeling method:

1. The proposed modeling method based on the developed hybrid models using fuzzy information facilitates an increase in the volume of more important target fractions of gasoline due to the use of the experience, knowledge, and intuition of DMs and experts. At the same time, as can be seen from the comparison results (Table 3), the volume of more important gasoline fractions of 180 °C and 180–220 °C from the outlet of the atmospheric block will increase by 1.5 and 1.1 tons/hour or 5.51 and 4.04%, respectively, while the volumes of less important products decrease. In addition, it is clear that the results of the proposed method more accurately coincide with real experimental data compared to known deterministic methods, which means high adequacy of the obtained models.

2. The proposed method, due to the use of fuzzy information, representing the experience, knowledge, and intuition of the DM, allows the fuzzy-described quality indicators of the produced target petroleum products ($\widetilde{y}_3,\ \widetilde{y}_8, \widetilde{y}_9, \widetilde{y}_{10}, \widetilde{y}_{11}, \widetilde{y}_{12}$), which are not determined by known methods, to be determined. As can be seen from the comparison results (Table 3), the obtained product quality values coincide with their real values determined in the laboratory by specialists. This means that the developed fuzzy models are adequate. In addition, the proposed system method for developing models of complex objects in conditions of shortage and fuzziness of the initial information allows us to synthesize linguistic models in conditions of fuzzy input and output production parameters.

3. When modeling based on the developed models at lower values of temperature and pressure in C-1 and C-2 (x_2, x_3, x_5 and x_5), the best values of output target products were obtained. Thus, the developed models allow one to obtain more target products with lower energy costs, which justifies their advantages over the known deterministic models.

The main limitations of the proposed approach to modeling the optimization of the coking process include the difficulties in assessing the degree of belonging of fuzzy parameters to fuzzy sets, adequately describing them, and some difficulties of the DM in the decision-making process. In the future, they can be eliminated by developing a special system for assessing the degree of belonging of fuzzy indicators to fuzzy sets and preparing and training the DM for the decision-making process. To develop this study, it is planned to automate and algorithmize the process of assessing and choosing the best solution as much as possible.

5. Conclusions

The problems of modeling and optimization of complex, poorly formalized technological processes are studied using the example of primary oil refining processes occurring in the atmospheric block under conditions of shortage and fuzziness of the initial information.

The main results of the study and conclusions include:

(1) A method for developing effective hybrid models of complex objects based on available statistical and fuzzy information has been developed, based on a systematic approach, methods of mathematical statistics, expert assessment, and theories of fuzzy sets. In this case, fuzzy information represents the experience, knowledge, and intuition of the DM and experts, expressed in natural language. Such a systemic application of various information, due to the synergism effect and the property of emergence, allows one to create effective models of complex, difficult-to-formalize production objects.

(2) Based on the proposed method for developing models of complex objects based on available information of various natures, hybrid models of the C-1 and C-2 atmospheric block columns of the primary oil refining unit have been developed.

(3) The primary oil refining process modeling results are compared with known models and the developed system of different models using additional fuzzy information. The advantages of the proposed approach are shown in comparison with the results of known deterministic models.

The novelty of the proposed system method and results lies in the effective use of knowledge, experience, and intuition of the DM, experts in developing models in conditions of shortage, and the fuzziness of the initial information. In addition, the proposed method allows for the development of more adequate models of production objects in conditions of shortage and fuzziness of the initial information based on the systematic use of available information of various natures.

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Abbreviations

EDP-AT	Electric desalination plant-atmospheric tubular
DM	decision-maker
GRF	gas reagent facilities
C-1	oil stripping rectification column
C-2	atmospheric column
BBP	beginning of the boiling point of the petroleum product fraction

Notations

y_j^M	the calculated values of the output parameters
y_j^E	experimental (real) values of the output parameters
R_D	permissible deviation
X, Y	universal sets, i.e., universes
~	means the fuzziness of the corresponding parameters and coefficients
$\wedge$	logical "and" sign
$\tilde{A}_i,\ i = \overline{1,n}, \tilde{B}_j,\ j = \overline{1,m}$	fuzzy subsets of input and output parameters of an object
$x_i,\ i = \overline{1,n}$	input, operating parameters of the object
$y_j,\ j = \overline{1,m}$	output parameters of the object
$\tilde{x}_i,\ i = \overline{1,n}$	fuzzy input, operating parameters of the object
$\tilde{y}_j,\ j = \overline{1,m}$	fuzzy output parameters of the object
$\tilde{R}_{ij}$	fuzzy mappings between input, output linguistic CTS variables
$\mu_{\tilde{R}_{ij}}\left(\tilde{x}_i, \tilde{y}_j\right)$	fuzzy relationship matrices describing fuzzy relationships
$\mu_{\tilde{B}_j}\left(\tilde{y}_j^*\right)$	membership functions of fuzzy output parameters of an object

Appendix A. Model for Assessing the Quality of Gasoline from Column C-1 Depending on the Input and Operating Parameters on the Sets of α-Level

$$\begin{aligned}\tilde{y}_3 = {} & \left(\frac{0.5}{17.171} + \frac{0.8}{17.875} + \frac{1}{18.010} + \frac{0.8}{18.010} + \frac{0.5}{18.020}\right) + \left(\frac{0.5}{0.284011215} + \frac{0.8}{0.284115347} + \frac{1}{0.284210524} + \frac{0.8}{0.284317517} + \frac{0.5}{0.284420025}\right)x_2 \\ & + \left(\frac{0.5}{29.825} + \frac{0.8}{29.980} + \frac{1}{30.015} + \frac{0.8}{30.115} + \frac{0.5}{30.123}\right)x_3 + \left(\frac{0.5}{0.000755} + \frac{0.8}{0.000877} + \frac{1}{0.000998} + \frac{0.8}{0.001157} + \frac{0.5}{0.001207}\right)x_2^2 \\ & + \left(\frac{0.5}{5.47} + \frac{0.8}{5.50} + \frac{1}{5.53} + \frac{0.8}{5.56} + \frac{0.5}{5.59}\right)x_3^2.\end{aligned}$$

Appendix B. Model for Assessing the Quality of Gasoline Fractions 180–220 °C from Column C-2 Depending on the Input and Operating Parameters on the Sets of α-Level

$$\begin{aligned}\tilde{y}_8 = {} & \left(\frac{0.5}{99.73} + \frac{0.8}{99.85} + \frac{1}{100.01} + \frac{0.8}{100.12} + \frac{0.5}{100.25}\right) + \left(\frac{0.5}{0.153846000} + \frac{0.8}{0.153846057} + \frac{1}{0.153846127} + \frac{0.8}{0.153846185} + \frac{0.5}{0.284420257}\right)x_5 \\ & + \left(\frac{0.5}{28.817} + \frac{0.8}{28.950} + \frac{1}{29.015} + \frac{0.8}{30.005} + \frac{0.5}{30.118}\right)x_6 \\ & + \left(\frac{0.5}{0.001183415} + \frac{0.8}{0.001183422} + \frac{1}{0.001183430} + \frac{0.8}{0.001183437} + \frac{0.5}{0.001183445}\right)x_5^2.\end{aligned}$$

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