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Development and Synthesis of Linguistic Models for Catalytic Cracking Unit in a Fuzzy Environment

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Abstract: This research develops a method for synthesizing linguistic models of fuzzy systems with fuzzy input and output parameters that are described by linguistic variables. Based on the proposed method, linguistic models of the Title 1000 catalytic cracking unit for heavy residues at the Shymkent oil refinery are developed, describing the dependence of the volume and quality of gasoline on the input and operating parameters of the facility, which are fuzzy. It is substantiated that the use of a fuzzy approach, which allows the use of the experience, knowledge, and intuition (intelligence) of the decision maker and subject matter experts, is the most suitable effective method for synthesizing models of complex, fuzzily described objects and processes for comparison with other methods. The main idea of the proposed work is to solve the problems of shortage and fuzziness of initial information when developing models and optimizing the operating modes of a catalytic cracking unit through the use of knowledge, experience, and intuition of experts in this field. To solve the problems of the shortage of initial quantitative information and the fuzziness of available information when developing mathematical models, it is proposed to systematically use statistical methods, expert assessment methods, and a heuristic method based on fuzzy logic. The scientific novelty of the research lies in the development of a method for synthesizing linguistic models in a fuzzy environment and an algorithm for its implementation, which makes it possible to describe the dependence of the fuzzy values of the object's output parameters on its fuzzy input and operating parameters. The proposed approach allows the formalization and synthesis of models of fuzzily described objects when other methods of model development are not applicable or do not give the expected results. The results of the work were simulated in the MATLAB Fuzzy Logic Toolbox.

Keywords: catalytic cracking process; linguistic model; fuzzy logic; computer modeling; optimization

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1. Introduction

The catalytic cracking unit is one of the main units of oil refineries designed for the production of high-quality automotive gasoline. The Shymkent Refinery operates a Title 1000 heavy residue catalytic cracking unit. The main process of this unit is the catalytic cracking of heavy residues. This is a fluidized bed process that converts heavy petroleum fractions into lighter and more valuable hydrocarbon products. The catalytic cracking process being examined at the unit is typical of many intricate, insufficiently formalized technological procedures. It is marked by uncertain initial data regarding the quality of the resultant gasoline, essential for refining models aimed at enhancing gasoline quality. In this regard, to describe the dependence of the quality of gasoline produced from a catalytic cracking unit, a very urgent task is to develop linguistic models in a fuzzy environment and methods for intellectualizing the process control system of the reactor–regenerator block of a catalytic cracking unit using linguistic models. At the same time, based on the representation of expert knowledge, it is necessary to automatically generate membership functions for the values of linguistic variables in conditions of fuzzy information, based on the experience, knowledge, and intuition of the decision maker (DM) and subject matter experts.

The results of the analysis of various sources [1–20] show that decision-making models developed taking into account fuzziness, based on fuzzy logic, are most effective for complex systems control under conditions of uncertainty. However, the issues of developing models in a fuzzy environment have not yet been sufficiently studied in research works. There is no method for synthesizing linguistic models in the conditions of fuzzy input and output parameters of the object. In this regard, the study of problems of the synthesis of effective linguistic models that allow solving decision-making problems for complex fuzzily described chemical-technological systems control remains an urgent task of modern science and practice.

The purpose of this study includes the following:

- Development of a method for synthesizing linguistic models of fuzzily described technological systems.
- Concepts for intellectualizing the process control system of the reactor–regenerator block of a catalytic cracking unit using developed linguistic models. At the same time, the effective use of expert knowledge with the automatic formation of membership functions for the values of linguistic variables in conditions of fuzzy information is based on the experience and intuition of experts.

As a result of the analysis of the principles and methods of developing mathematical models, decision making, and optimization of industrial objects, it was revealed that scientific works do not sufficiently cover the issues of developing linguistic models and optimizing their operating modes. In [1,2], approaches to the development of mathematical models and optimization of parameters of technological objects, which are characterized by the fuzziness of the initial information, were studied and proposed. Since 2010, several works by authors R.A. Aliev, N.R. Yusupbekov, M.F. Azeem, H. Taskin, and P.B. Osofisan have been published using fuzzy logic methods in catalytic cracking control algorithms.

Works [3,4] focus on developing a model of the catalytic cracking process sensitive to the composition of the raw material and the properties of the catalyst. We agree that these indicators affect the yield and quality of gasoline, but they relate to the chemical properties of the raw materials and catalyst. To achieve the goal, it is not enough to regulate the above parameters; it is necessary to additionally regulate such parameters as the temperature and pressure of the reactor, the temperature of the regenerator, and the consumption of raw materials and catalyst, which are the key controlled parameters of the control object. It is also necessary to take into account that process parameters may be fuzzy. In this regard, there is a need to develop linguistic models of a catalytic cracking unit that take into account fuzzy input and output parameters described by linguistic variables, studied by our proposed method for their synthesis. This method allows using the experience, knowledge, and intuition of experts in the field.

The article [5] proposes to solve the problem using kinetic modeling and structural grouping of components. These methods require accurate and extensive data for model verification. When data are insufficient or uncertain, models may be inaccurate. Kinetic modeling and structural grouping methods have their own advantages, such as high accuracy and detail in the presence of high-quality data. However, compared to fuzzy logic, they are less flexible, difficult to adapt to new conditions, and require significant computing resources. Fuzzy logic, in turn, provides greater flexibility and adaptability, especially in conditions of uncertainty and lack of data, while integrating expert knowledge and intuition.

In [6], the authors solve the problem using hybrid modeling, which depends on accurate quantitative data. A hybrid model based on structural grouping and the analogy method is highly accurate in the presence of high-quality data and can effectively optimize real-time processes. The works [7,8] use artificial intelligence methods based on big data, machine learning, and deep learning, which require large volumes of high-quality data for training models. Lack of data or poor data quality can significantly reduce the accuracy and reliability of these models. Also, the above models are less flexible, difficult to adapt, and require significant computing resources. Fuzzy logic, on the contrary, provides greater flexibility and adaptability, especially in conditions of uncertainty and insufficient data, and effectively integrates expert knowledge, making it a more universal and less resource-intensive method for modeling and optimizing complex systems.

However, in these and other analyzed works devoted to the modeling and optimization of complex, fuzzily described objects, the issues of developing nonlinear models with fuzzy input and output parameters of the object have not been sufficiently studied. In addition, in the known methods for solving fuzzy modeling and optimization problems, at the formulation stage, the fuzzy problem is transformed into a set of crisp problems and is then solved using existing crisp methods. With this approach, a significant part of the initial collected fuzzy information (knowledge, experience of experts) is often lost, which leads to a decrease in the adequacy of the application of the resulting models and solutions to reality [9,10].

Fuzzy logic is a systematic mathematical formulation for the study and characterization of processes with varying levels of uncertainty due to the fuzziness of the available information. This is the best choice when the mathematical model of the process is too complex to be evaluated quickly enough in real-time. Fuzzy logic is widely used in modern research for complex systems control like a robotic manipulator [11]. The use of fuzzy logic allows modeling systems with fuzzy input and output parameters, which may be difficult to implement with other methods. This is especially important in conditions of a shortage of quantitative information. Incorporating the experience, knowledge, and intuition of experts into the modeling process increases the accuracy and reliability of models, which can be especially useful in complex and poorly formalized systems. The use of a fuzzy approach allows the problems of the shortage and fuzziness of initial information to be effectively solved. This makes the method more flexible and adaptable to different conditions and scenarios. The development of a fuzzy inference rule base and a knowledge base for a decision-making system improves the control of technological objects in real-time and allows a prompt reaction to changes in the production process. The systematic use of statistical methods, expert assessment methods, and a heuristic method based on fuzzy logic provides an integrated approach to solving modeling problems.

In [12], the problems of developing models of a reactor block of a catalytic cracking unit operating at the Atyrau oil refinery in a fuzzy environment were investigated and solved. The developed models in a fuzzy environment take into account the influence of only two input variables (raw material supply rate and reactor temperature) on one output parameter—the volume of catalyzate (produced product). In addition, the rule base for fuzzy modeling consists of only nine basic rules, i.e., the proposed approach to developing a fuzzy model is limited and is not universal.

In this paper, a method for synthesizing linguistic models is developed and its algorithmic block diagram is presented, demonstrating the universality of the approach to the development of linguistic models of various objects and processes in a fuzzy environment. Based on the proposed method, linguistic models of the Title 1000 heavy residue catalytic cracking unit at the Shymkent oil refinery are synthesized, describing the dependence of the volume and quality of gasoline (its density), which are important parameters for this object, on six input operating parameters, which are fuzzy.

The input operating parameters that quite strongly influence the volume and density of benzine from the output of the Title 1000 heavy residue catalytic cracking unit of the Shymkent oil refinery are: 1—raw material consumption—x_1, 2—raw material density—x_2, 3—raw material temperature—x_3, 4—temperature in the reactor—x_4, 5—pressure in the reactor—x_5, and 6—catalyst consumption—x_6. The volume of the created rule base in this work includes 20 fuzzy inference rules, i.e., they cover more widely possible options, and changes in input and operating parameters.

Based on the analysis results of known methods for modeling catalytic cracking processes, it was established that they generally have restrictions and are ineffective for modeling under conditions of uncertainty. Many well-known methods are usually oriented towards modeling under deterministic conditions, i.e., when there are unambiguous dependencies between the input operating and output parameters of the object of catalytic cracking units. For example, in works [6,13–18], methods for dynamic modeling of catalytic cracking processes and approaches to developing their models under deterministic conditions were studied, but the problems of uncertainty that often arise in practice when developing models of catalytic cracking units were not considered. As is known in practice, in many cases, catalytic cracking units, like many other production objects, operate under uncertain conditions caused by the initial data's randomness and fuzziness.

Studies [19–22] propose approaches to modeling catalytic cracking units under conditions of uncertainty that arise due to the random, stochastic nature of the object's parameters. In these and other similar studies, the problems of uncertainty caused by the stochasticity of the values of the object's parameters are solved based on the methods of probability theories and mathematical statistics. However, uncertainty is often caused due to the fuzziness of the object parameters necessary for developing models. In these situations, stochastic methods for solving problems of uncertainty are not suitable, since there are no measurable, quantitative, or statistical data, and the available information is characterized by fuzziness, which represents the experience, knowledge, and intuition of experts, expressed in natural language. Thus, in these situations, to model the operation of catalytic cracking units and other production objects, it is necessary to use a fuzzy approach based on the methods of expert assessments and fuzzy sets.

Recently, research aimed at modeling complex, fuzzily described production objects such as catalytic cracking units based on a fuzzy approach has intensified. For example, in works [13,20,23–26], approaches to modeling and control of catalytic cracking units and other objects with fuzzy initial data based on fuzzy logic and artificial intelligence methods, neural network technologies were investigated and proposed. These and other similar works consider the problems of partial fuzziness of parameters, i.e., fuzzy output parameters of objects, when input operating parameters are considered crisp. In this case, the proposed approaches are based on the α-level set, and make it possible to transform fuzzy models on the α-level set to a set of crisp models. Thus, the developed fuzzy model is presented as being approximately equivalent to crisp models, the number of which depends on the number of α-level sets.

Then, using known methods of parametric identification, unknown fuzzy parameters are determined on the α-level set, which, when combined according to the appropriate formula of the fuzzy sets theory, have one crisp value. However, in this approach, the problems of fuzziness are solved only partially, and the adequacy of the developed model is significantly reduced, since a significant part of the collected fuzzy information is lost and not used. Essentially, the collected fuzzy information, based on knowledge, experience, and intuition, i.e., the intelligence of experts, is used only at the points at which the α-levels intersect the membership functions describing the fuzzy parameters. This is the main disadvantage of approaches to solving fuzziness problems based on multiple α-levels. In practice, the input operating and output parameters of the modeled object are often fuzzy, for which the described approach is not applicable. Therefore, it is necessary to develop a linguistic modeling method that allows, when the input operating and output parameters of an object are fuzzy, the use of the collected fuzzy information, to synthesize linguistic models, which makes it possible to effectively model objects in a fuzzy environment. The main contribution of this paper is the development of a method for synthesizing such linguistic models of the catalytic cracking unit at the Shymkent oil refinery, which makes it possible to effectively simulate and determine the best mode of its operation in a fuzzy environment. At the same time, this work demonstrates how to effectively apply existing fuzzy logic tools based on the Fuzzy Logic Toolbox application. In our case, the output value of gasoline density is a fuzzy output parameter that is not measured in production by a measuring device and is not determined using traditional measurement and control methods [27,28]. Therefore, it is determined through laboratory research with the participation of a human specialist based on his experience and knowledge, which they are described by fuzziness. It is known that the processes of industrial facilities are nonlinear, independent of time, and full of uncertainties, which makes them very difficult to model, control, and manage. For such processes, conventional PID controllers become ineffective, since they require good mathematical formalization [29,30].

Moreover, the catalytic cracking unit continues to play a key role in any refinery as a unit for deep processing of oil and petroleum products. For many refineries, they are the key to profitability. The successful operation of the unit determines whether a refinery can remain competitive in today's market. The main purpose of the unit is to convert straight-run fuel oil or a mixture of straight-run fuel oil and vacuum gas oil into high-quality high-octane gasoline. A large amount of coke is formed as a by-product. Coke deposits on the catalyst and reduces its activity. Lighter hydrocarbon products are separated from the spent catalyst in the reactor. Steam is supplied to remove volatile hydrocarbons from the catalyst. The catalyst is then returned to the regenerator, where the coke is burned when exposed to air. This usually occurs by partial or complete combustion. The regenerated catalyst is then circulated back to be mixed with the incoming feedstock from the crude oil processing unit [31]. Parameter selection also plays a critical role in the performance of the catalytic cracking unit. There is a lot of discussion about the correct choice of variables for fuzzy optimization objects [32,33]. However, the focus of this article is on the key variables that can be used to control the catalytic cracking process to achieve the desired results (production of high-quality gasoline with a density of no more than 0.737 t/m^3). These variables can be classified as input, output, or disturbance. The input variables are consumption, density, raw material temperature, reactor temperature and pressure, and catalyst consumption. The output variables are gasoline yield (a quantitative indicator) and gasoline density (a qualitative indicator). Depending on the variables chosen, results may vary. The dependence of the input and output variables of the unit as a control object and the results were studied in [34].

The novelty of this research compared to other sources is the development of an effective method for synthesizing linguistic models of fuzzily described objects. Data and information for the development of linguistic models are obtained using expert assessment methods, which are formalized and processed based on the methods of fuzzy set theories. Based on the developed method for synthesizing linguistic models, linguistic models of the reactor–regenerator block of the Shymkent oil refinery catalytic cracking unit, which is the object of the study, are developed. The adequacy of the developed models is checked by comparing the output data obtained from the developed models and the corresponding real data obtained from the object of study based on experiments. The developed linguistic models are implemented in the fuzzy logic tool of the MATLAB system. The resulting linguistic models are one of the main elements of an intellectual decision-making system (IDSS), which allows making effective decisions on managing complex, fuzzily described objects.

As a result of analysis and comparison of the current level of development of methods and modeling results in conditions of data uncertainty, the following was established:

- Currently, research has not yet solved the problems of developing linguistic models of fuzzily described production objects with fuzzy input operating and output parameters.
- Existing approaches to solving the problems of developing models of fuzzily described objects under conditions of uncertainty due to the fuzziness of the initial information have been developed mainly for objects with crisp input operating and fuzzy output parameters. These approaches are based on transforming the original fuzzy model

into a set of crisp models using the α-level set of the fuzzy set theories. However, the developed models of fuzzy objects based on this approach have low adequacy since a significant part of the collected fuzzy information (experience, knowledge, intuition of experts) is lost during the transformation process. Therefore, it is very important and relevant to develop and apply methods for producing models with fuzzy input operating and output parameters of an object, allowing the synthesizing of adequate, effective models based on the maximum use of the collected fuzzy expert information.

The principal value and importance of this article's results and presented statements lies in developing a method for synthesizing linguistic models, using effective linguistic models of objects in a fuzzy environment. The developed linguistic models of the catalytic cracking unit at the Shymkent oil refinery allow for the modeling of various operating modes and the selection of the most effective operating modes of the object under study. These and other research results justify the theoretical value and importance of developing modeling methods in a fuzzy environment with fuzzy input and output data. The results of the obtained linguistic models of the object under study using the Fuzzy Logic Toolbox show their practical significance and the ability to apply the proposed linguistic modeling approach for other objects with fuzzy input and output parameters.

2. Materials and Methods

The object of study of this work is the reactor–regenerator unit of the Title 1000 heavy residue catalytic cracking unit of the Shymkent oil refinery (Shymkent, Kazakhstan). The Title 1000 heavy residue catalytic cracking unit is designed to produce high-octane components of motor gasoline and liquefied hydrocarbon gases through the process of catalytic cracking of straight-run fuel oil (C-100) or a mixture of fuel oil and vacuum gas oil at high temperatures and moderate pressure, in the presence of a fluidized circulating highly dispersed aluminosilicate-based catalyst. The main technological process takes place in the reactor–regenerator block of the unit. The sections of this block are the reactor and the regenerator, which are closely interconnected. The main cracking process occurs in the reactor by adding a catalyst to the unit feedstock. As a result of cracking, coke is formed, which reduces the activity of the process. The resulting coke on the catalyst is burned off during the regeneration process.

Figure 1 shows a technological diagram of the reactor–regenerator block of the catalytic cracking unit at the Shymkent oil refinery.

The process flow diagram (Figure 1) includes a comprehensive catalytic cracking system, including a reactor, regenerator, heat exchangers, and control systems for efficiently converting raw materials into gasoline. The focus is on maintaining temperature and pressure, as well as catalyst regeneration and control to maintain the efficiency of the cracking process. Fuzzy logic is used to control process parameters such as the reactor's temperature, regenerator, reactor pressure, supply of raw materials and catalyst, and regulation of other main parameters of the system. The goal is to optimize product yield and maintain the required product quality. To achieve the goal, fuzzy rules are created based on a survey of subject area experts.

Fuzzy logic is a system that simulates human expert decisions. Thus, it is intuitively easy for people to understand and apply it in engineering and non-engineering applications. The results of fuzzy logic do not require further elaboration or explanation because the results are often described in terms that are easy for anyone to understand. Implementing fuzzy logic requires the knowledge and experience of an expert. The experience is written in a rule-based format, which is used to create a database as well as fuzzy rules. The more precise the rules, the more applicable the results will be. It should be noted that these rules are approximate; this is the same as human decisions. The human expert can be replaced by a combination of a fuzzy rule-based block system called a defuzzifier. The sensory crisp data are then transferred to a system where physical values are represented or compressed into heuristic variables based on appropriate membership functions. These linguistic variables will then be used in if–then conditions and will be modified, and revised to a crisp (numerical) result that is an approximation of the actual result $y(t)$ in the defuzzification process. The key point of fuzzy logic is that it does not require deep knowledge about the object itself or how processes occur within it, which is necessary for the use of PID controllers [33,35].

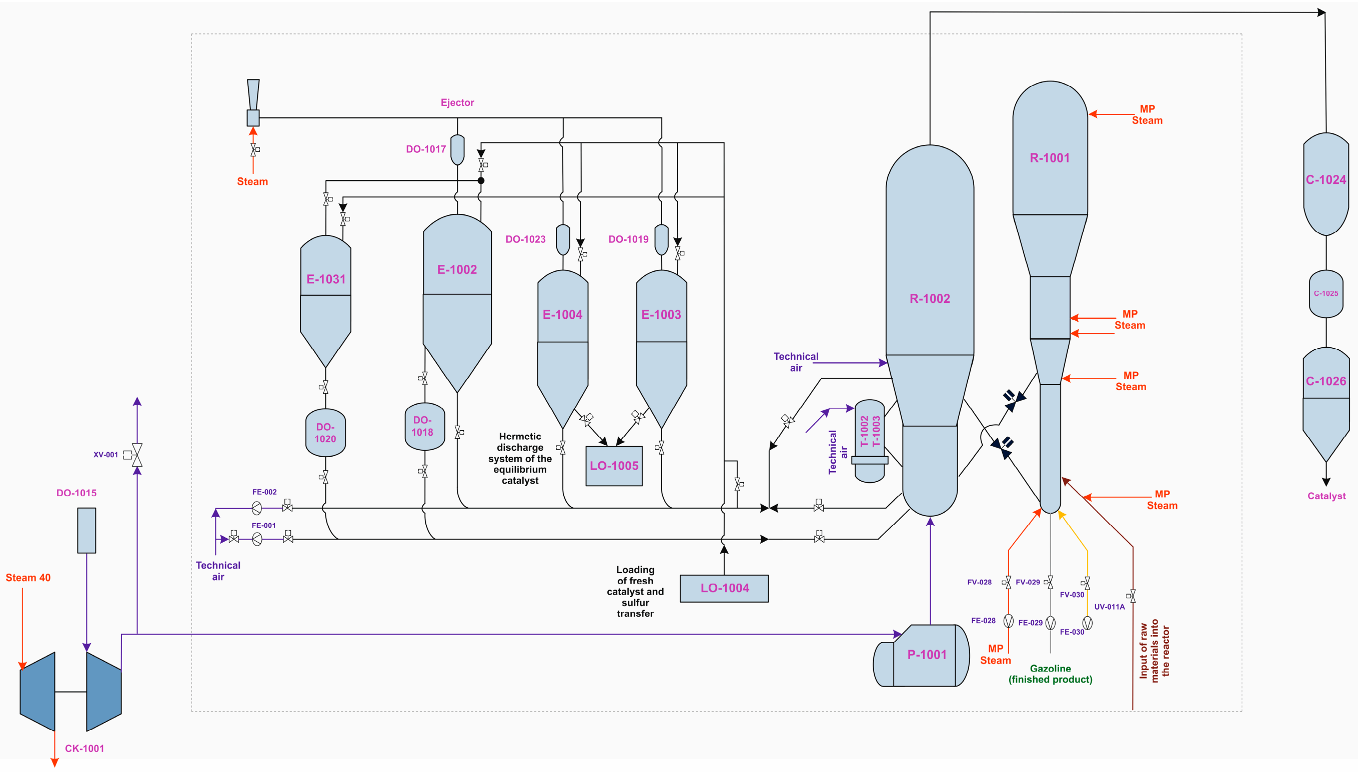

Figure 1. Technological process flow diagram of the reactor–regenerator block of the Title 1000 catalytic cracking unit.

The proposed method for synthesizing linguistic models with fuzzy input and output parameters of a reactor–regenerator unit is based on methods of expert assessments and the rule of fuzzy conditional inference.

Fuzzy logic, which serves to implement fuzzy control methods, more naturally describes the nature of human thinking and the course of its reasoning than traditional formal logical systems. That is why the use of mathematical tools to represent fuzzy initial information allows us to build models that most adequately reflect various aspects of uncertainty. Linguistic uncertainty is associated with the inaccuracy of the description of the situation or event itself, regardless of the time of its consideration [36].

Probability theory cannot be used to solve such problems since ideas about the subjective categories present in human thinking processes are not fully consistent with its axioms.

Method for synthesis of linguistic models. A block diagram of the developed method for synthesizing linguistic models based on fuzzy input and output parameters of an object is shown in Figure 2. We provide a detailed description of the main blocks of the algorithm for implementing the developed method for synthesizing linguistic models of objects in a fuzzy environment with fuzzy input operating and output parameters. In block 2, fuzzy input and process parameters $\widetilde{x}_i$, $i = \overline{1,n}$, are selected to influence the optimized output parameters $\widetilde{y}_j$, $j = \overline{1,m}$, which are also fuzzy. In blocks 3 and 4, the terms and universes of the selected levels $\widetilde{x}_i$ and $\widetilde{y}_j$ are defined. In this case, terms (fuzzy sets) are fuzzy descriptions of the values of the corresponding levels of parameters, and universes are the intervals of their numerical display.

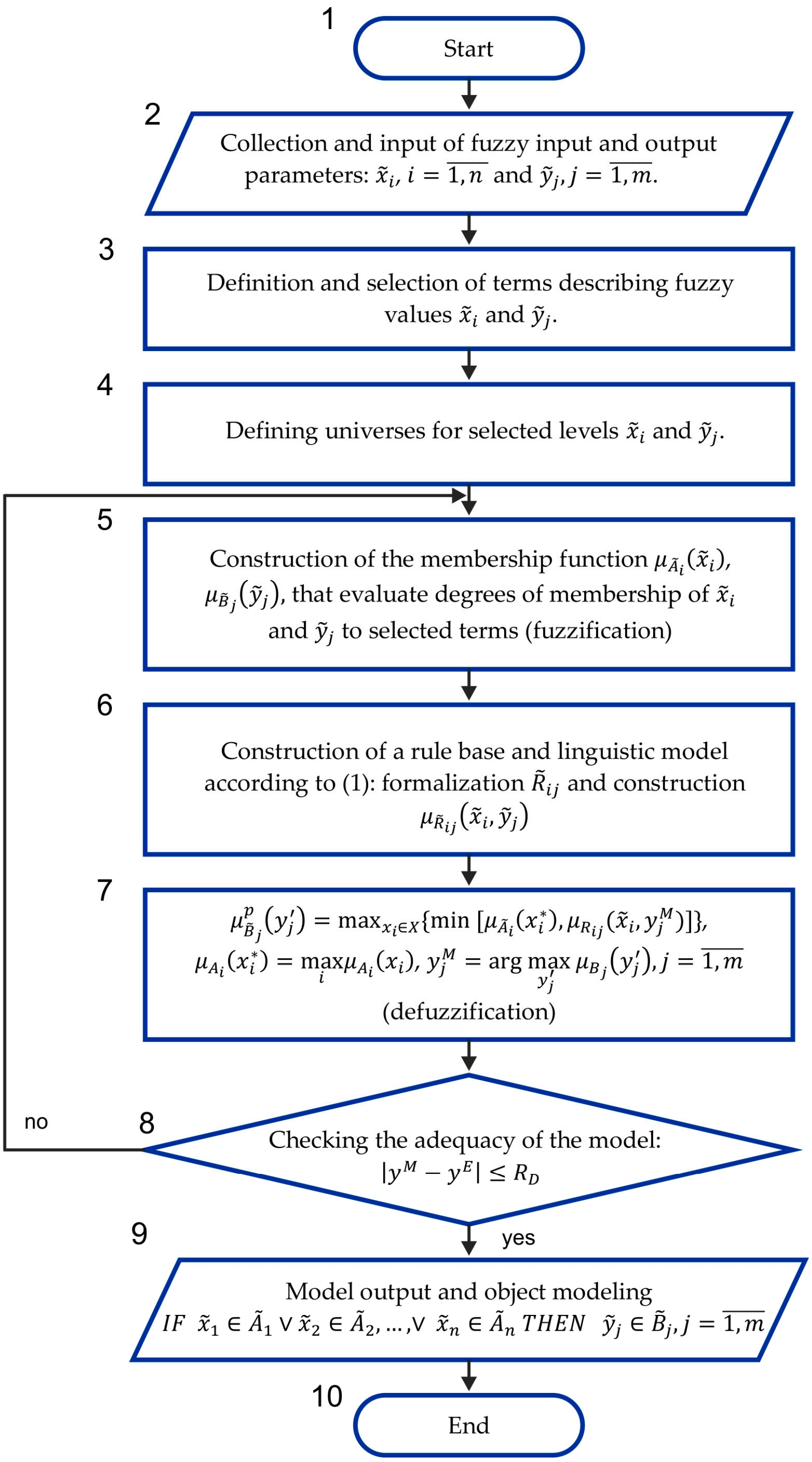

Figure 2. Block diagram of the implementation algorithm of the developed method for synthesizing linguistic models.

In block 5, the fuzzification procedure is implemented, i.e., membership functions are constructed that describe the degrees of membership in fuzzy sets (terms). In this case, it is recommended to build membership functions using the Fuzzy Logic Toolbox application of the MATLAB system (version 7.0). In block 6, a rule base and linguistic models are built, consisting of logical rules for conditional inference:

$$IF\ \tilde{x}_1 \in \tilde{A}_1 \vee \tilde{x}_2 \in \tilde{A}_2, \ldots, \vee \tilde{x}_n \in \tilde{A}_n\ THEN\ \tilde{y}_j \in \tilde{B}_j, j = \overline{1,m}. \quad (1)$$

Linguistic models verbally describe the influences of fuzzy $\widetilde{x}_i$, $i = \overline{1,n}$ on $\widetilde{y}_j$, $j = \overline{1,m}$ and are built based on a rule base, which is determined based on expert assessment methods and fuzzy set theories. For convenience, the rule base can be presented as a table in which, using term sets (selected in block 3), fuzzy values of input and operating parameters $\widetilde{x}_i$ and the corresponding fuzzy values of output parameters $\widetilde{y}_j$ are given.

Based on the table in Figure 2, it is possible to formalize fuzzy mappings $\widetilde{R}_{ij}$, that allow us to determine the relationship between linguistic input and output parameters $\widetilde{x}_i$ and $\widetilde{y}_j$.

For a p-level term from term sets, the fuzzy mapping is defined as the Cartesian product of the corresponding universal sets: $\widetilde{R}_{ij}^{p} = \widetilde{A}_i^{p} \times \widetilde{B}_j^{p}$. To carry out calculations, it is necessary to construct matrices of fuzzy relations $\mu_{\widetilde{R}_{ij}}\left(\widetilde{x}_i, \widetilde{y}_j\right)$ based on the membership functions of the fuzzy mapping $\widetilde{R}_{ij}\mu_{\widetilde{R}_{ij}}\left(\widetilde{x}_i, \widetilde{y}_j\right)$. In general, such a matrix for a p-level term has the following form:

$$\mu_{\widetilde{R}_{ij}}\left(\widetilde{x}_i, \widetilde{y}_j\right) = min\left[\mu^{p}_{\widetilde{A}_i}(x_i), \mu^{p}_{\widetilde{B}_j}(y_j)\right], i = \overline{1,n},\ j = \overline{1,m}.$$

In block 7 of the method, to determine a set of fuzzy values of the output parameters of the process, the compositional inference rule can be used:

$$\widetilde{B}_j = \widetilde{A}_i \circ \widetilde{R}_{ij}, \tag{2}$$

where $\widetilde{A}_i \subset X, \widetilde{B}_j \subset Y$, and X, Y—universal sets, i.e., universes.

Based on this rule, the values of the membership function of the output parameters can be determined using the following formula:

$$\mu^{p}_{\widetilde{B}_j}\left(y'_j\right) = \max_{x_i \in X}\{\min[\mu_{\widetilde{A}_i}(x_i^*), \mu_{R_{ij}}(\widetilde{x}_i, y_j^M)]\}. \tag{3}$$

In Formula (3) x_i^* denotes the fuzzy values of operating parameters assessed by experts. Then the desired set, in which the current values of the operating parameters belong, is determined by the formula $\mu_{A_i}(x_i^*) = \max\mu_{A_i}(x_i)$, i.e., as a set in which the values of the operating parameters have the maximum value of the membership function.

To defuzzify the results, i.e., determine the numerical values of the output parameters y_j^M from a set of fuzzy solutions, the following expression can be applied: $y_j^M = \arg\max_{y'_j} \mu_{B_j}\left(y'_j\right)$, $j = \overline{1,m}$. Thus, the numerical values of the output parameters are selected as an argument for the maximum value of the membership function of the output parameters. The application of the described approach to determining the numerical value of the output parameter y_j^M is justified in the case of an acute form of the membership function in the area of the maximum value. If the graph of the membership function in the area of the maximum value contains many points with similar values, their average value can be chosen as the numerical value of the output parameter y_j^M.

The novelty of the developed and used method for synthesizing linguistic models with fuzzy input, mode, and output parameters of the object under study lies in the following:

- The developed method for synthesizing linguistic models of fuzzily described objects using linguistic variables based on expert assessment methods, theories of fuzzy sets, and fuzzy rules of conditional inference is presented as a specific algorithm for its implementation. There are no specific algorithms for their synthesis in the well-known works in which linguistic models are studied; only general ideas about such models are given. In this work, based on a systematic approach, with the help of various methods of collecting, formalizing, and using fuzzy information and rules, the proposed method for synthesizing linguistic models was applied to a specific algorithm that allows it to be effectively used for the synthesis of linguistic models.

- Using the algorithm for implementing the proposed method for synthesizing linguistic models constructed in Figure 2, linguistic models of the catalytic cracking unit at the Shymkent oil refinery, the object of this research, were synthesized. The resulting linguistic models make it possible to effectively model various object operation modes in this research in a fuzzy environment. The novelty and effectiveness of the synthesized linguistic models of the catalytic cracking unit under study are confirmed by the excellent consistency of the obtained model results with the presentation of experts and with the actual data of the research object as a result of the experiments performed.

Thus, the proposed algorithm for implementing the developed method contributes to developing and expanding the theory and methods of modeling complex, fuzzily described production objects. The developed method for synthesizing linguistic models of fuzzily described objects with fuzzy input and output parameters is of practical importance since it allows, by fuzzy modeling, many production objects to determine the effective mode of their operation.

3. Results

Statistical data were taken from the technological regulations of the Title 1000 heavy residue catalytic cracking RFCC unit of the Shymkent oil refinery. To model the operation of the unit, and its input and operating parameters, those independent variables were selected that affect the operating modes and the output parameters of the unit, which are the optimized parameters of the object (product yield and quality).

The input parameters of the model are: x_1—raw material consumption, x_2—raw material density, x_3—raw material temperature, x_4—reactor temperature, x_5—reactor pressure, and x_6—catalyst consumption. The following parameters are accepted as output parameters of the model: y_1—gasoline output and y_2—gasoline density. Table 1 shows the main variables in the unit process, including controlled and measured variables.

Table 1. Main process parameters.

Parameter Name	Parameter Designation
Raw material consumption	x_1, t/day
Raw material density	x_2, t/m^3
Raw material temperature	x_3, C
Reactor temperature	x_4, C
Reactor pressure	x_5, kgf/cm^2
Catalyst consumption	x_6, t/day
Gasoline yield	y_1, %
Gasoline density	y_2, t/m^3

When constructing a fuzzy production model, the listed technological parameters are interpreted as linguistic variables of the following form:

$$\overset{\circ}{X}_i = \left\{ \left\langle X_i^j U_{x_i}, \widetilde{X}_i \right\rangle \right\},\ X_i^j \in T_i^*(u),\ i = \overline{1,6};$$

$$\overset{\circ}{Y}_l = \left\{ \left\langle Y_l^k, V_{Y_l}, \widetilde{Y} \right\rangle_l \right\},\ Y_l^k \in T_l^*(u),\ l = \overline{1,2}$$

where U_{x_i}, V_{Y_j}—universes.

$$\widetilde{X}_i = \int\limits_{U_{X_i}} \mu_{X_i}(u)/u,\ i = \overline{1,6}; \qquad \widetilde{Y}_l = \int\limits_{V_{Y_l}} \mu_{Y_l}(v)/v,\ l = \overline{1,2}$$

Fuzzy sets described by membership functions:

$$\mu_{X_i}(u);\ U_{X_i} \to [0,\ 1];\ \mu_{Y_l}(v);\ V_Y \to [0,\ 1];\ T_i^*(u),\ T_l^*(v)$$

Extended term sets of linguistic variables with the same names as parameters, respectively, for the input and output of the unit; j, k—indices of the corresponding numbers of linguistic terms specified in Table 2.

Table 2. Terms of linguistic variables and their abbreviations for constructing their membership functions and forming a rule base.

Terms of Fuzzy Parameters	Designation
L	significantly below the norm
BA	below average
A	Average
AA	above average
H	significantly higher than the norm

In contrast to traditional control methods, fuzzy logic circuits provide a more efficient method for analyzing and controlling nonlinear, time-varying systems that are relatively complex and difficult to model mathematically [36]. The fuzzy logic controller allows the general characteristics of a nonlinear system to be expressed through linguistic expressions by creating if–then rules [37].

Fuzzy logic is a language that allows complex natural language sentences to be translated into mathematical formalism. Knowledge is acquired and processed inferentially and deductively through symbolic reasoning [38].

A fuzzy controller determines the behavior of variables and their relationships with each other by creating dynamic nonlinear graphs known as surface graphs. Six input and two output variables are selected based on their importance and significance level in the process and all the factors influencing the unit's operating modes and outputs. Measurement and control parameters are also defined to optimize the unit.

When creating a rule-based fuzzy system, the following steps are performed to process the rules for the fuzzy controller:

- Input and output variables and ranges of their values are determined;
- A fuzzy membership function of degrees of truth is created;
- A rule base for controller design is created;
- Interaction of rules is defined;
- Rules merging is executed.

Let us consider the results of applying the algorithm to identify, using a fuzzy observation model, the main indicators of the technological process occurring in the reactor–regenerator block of a catalytic cracking unit. Clustering data for membership functions are shown in Table 2. Based on "historical" data on changes in the values of technological parameters used in controlling the cracking process, membership functions were created for the linguistic terms, for each output variable of the technological process coordinates, as follows: L—significantly below the norm; BA—below average; A—average; AA—above average; H—significantly higher than the norm. For each variable, five terms were taken, which makes it possible to control both minor and significant deviations from the normal operating mode and to form, by the algorithm, proportional control of the position of the valves at the inlet and outlet of the reactor. As the number of terms increases, the number of logical rules increases, which increases the probability of an error in control decision making. This can lead to a decrease in the quality of control according to the algorithm that uses the results of object identification by the method under consideration.

The knowledge base contains all the inference rules based on the production model of knowledge representation (if–then), characterizing the goals and policies used by experts to implement management. An inference engine refers to a computational procedure used to evaluate fuzzy rules. This is the core of fuzzy logic control as it is responsible for executing the knowledge base by generating responses.

The base of rules and knowledge was created with the involvement of the decision maker (DM), who manages the work of the research object, and experts from the ShOR. As a result of a survey of DM and experts, a range of values of fuzzy parameters was determined and configured according to Table 3. The rules were configured using the technical regulations of the plant.

Table 3. Range of values of fuzzy parameters x_1, x_2, x_3, x_4, x_5, x_6, y_1, y_2.

Variables	L	BA	A	AA	H
x_1	0–100	120–160	180–240	260–320	320–400
x_2	0.4–0.5	0.6–0.7	0.8–0.9	1–1.2	1.3–1.6
x_3	0–180	190–205	210–215	220–235	240–255
x_4	0–440	450–475	480–542	550–570	570–600
x_5	0.5–0.9	1–1.4	1.53–2.6	2.7–2.9	3–3.5
x_6	1480–1580	1580–1670	1680–1790	1800–1900	1910–1990
y_1	0–35	38–47	48–50	50–55	56–70
y_2	0.43–0.525	0.53–630	0.635–0.735	0.74–0.84	0.85–0.95

A base of fuzzy production models of the actions of the operator-technologist (DM) managing the technological process was formed. The list of rules connecting fuzzy input variables with fuzzy output parameters of an object is given below. These rules were implemented in the fuzzy rules editor Fuzzy Logic Toolbox of MATLAB to create logical inference and a nonlinear surface model. The number of compiled rules transmitted to the system in the form of fuzzy rules is limited in such a way that only those rules that affect the catalytic cracking process were taken into account.

If (x_1 is L) and (x_2 is L) then (y_1 is L)(y_2 is L)
If (x_1 is L) and (x_2 is A) then (y_1 is L)(y_2 is A)
If (x_1 is A) and (x_2 is A) then (y_1 is A)(y_2 is A)
If (x_1 is BA) and (x_2 is A) then (y_1 is BA)(y_2 is A)
If (x_1 is A) and (x_2 is AA) then (y_1 is A)(y_2 is AA)
If (x_1 is H) and (x_2 is H) then (y_1 is H)(y_2 is H)
If (x_1 is H) and (x_2 is L) then (y_1 is AA)(y_2 is BA)
If (x_4 is H) and (x_6 is L) then (y_1 is H)(y_2 is L)
If (x_4 is L) and (x_6 is H) then (y_1 is L)(y_2 is H)
If (x_4 is BA) and (x_6 is A) then (y_1 is BA)(y2 is A)
If (x_4 is A) and (x_6 is BA) then (y_1 is A)(y_2 is BA)
If (x_4 is AA) and (x_6 is AA) then (y_1 is AA)(y_2 is AA)
If (x_2 is L) and (x_5 is L) then (y_1 is L)(y_2 is L)
If (x_2 is BA) and (x_5 is A) then (y_1 is L)(y_2 is BA)
If (x_2 is AA) and (x_5 is BA) then (y_1 is AA)(y_2 is AA)
If (x_3 is L) and (x_5 is L) then (y_1 is H)(y_2 is H)
If (x_3 is BA) and (x_5 is L) then (y_1 is AA)(y_2 is H)
If (x_3 is AA) and (x_5 is BA) then (y_1 is BA)(y_2 is BA)
If (x_3 is A) and (x_5 is BA) then (y_1 is AA)(y_2 is AA)
If (x_3 is H) and (x_5 is L) then (y_1 is H)(y_2 is L)

Figures 3–10 show the eight membership functions used in this study. Since the system is nonlinear, the Gaussian type of membership function was chosen to more effectively reflect the membership function. The system works with fuzzy sets that do not have ideally defined boundaries, with a gradual transition between the membership and non-membership of variables in a given set. Membership functions enable modeling of flexibility through the use of linguistic variables. The first step in the fuzzy inference process is fuzzification. This is responsible for converting inputs into fuzzy information that the inference engine can understand and process. In a transformation, each input has its own set of membership functions. These functions must be representative for the variable; hence, they cover all possible input values.

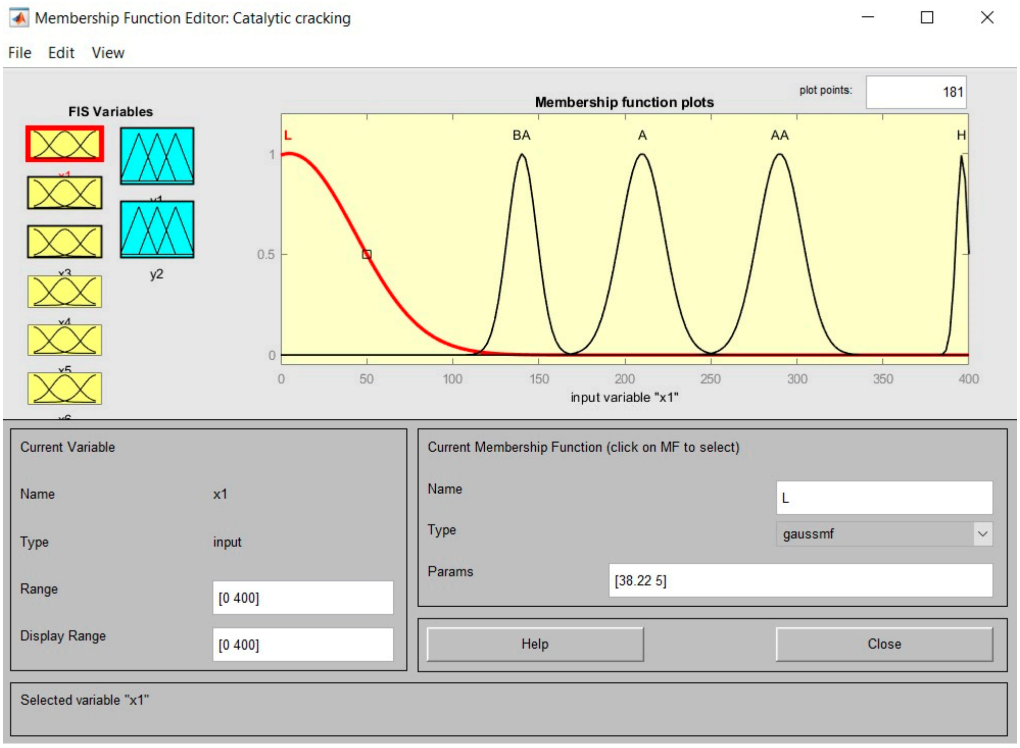

Figure 3. Raw material consumption membership function.

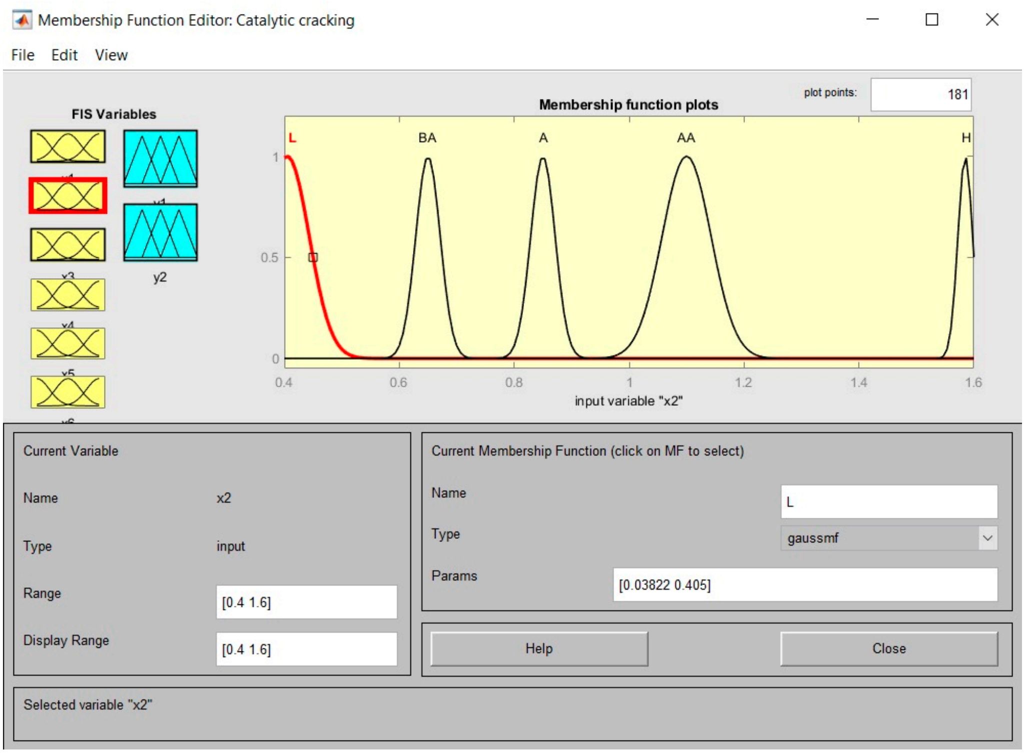

Figure 4. Raw material density membership function.

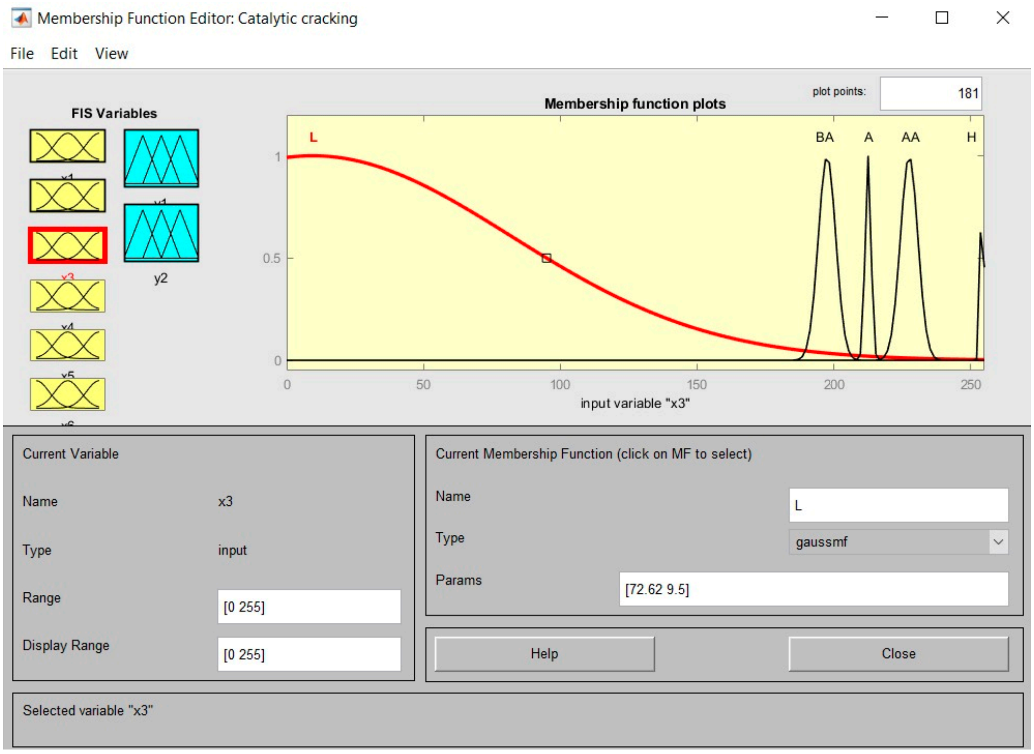

Figure 5. Raw material temperature membership function.

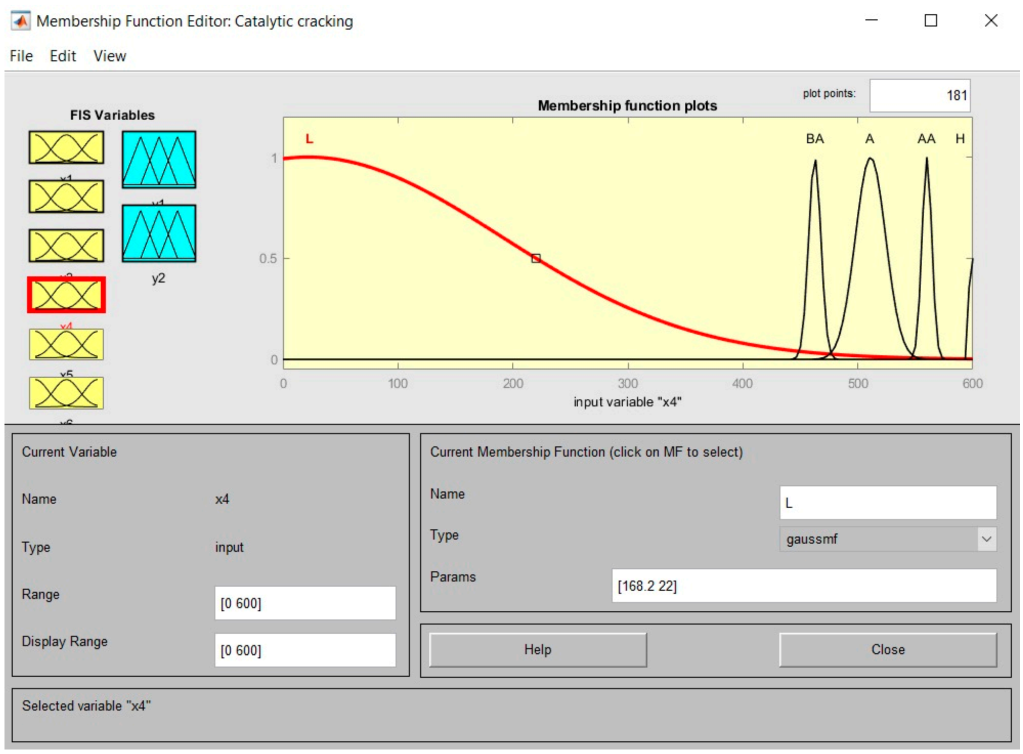

Figure 6. Reactor temperature membership function.

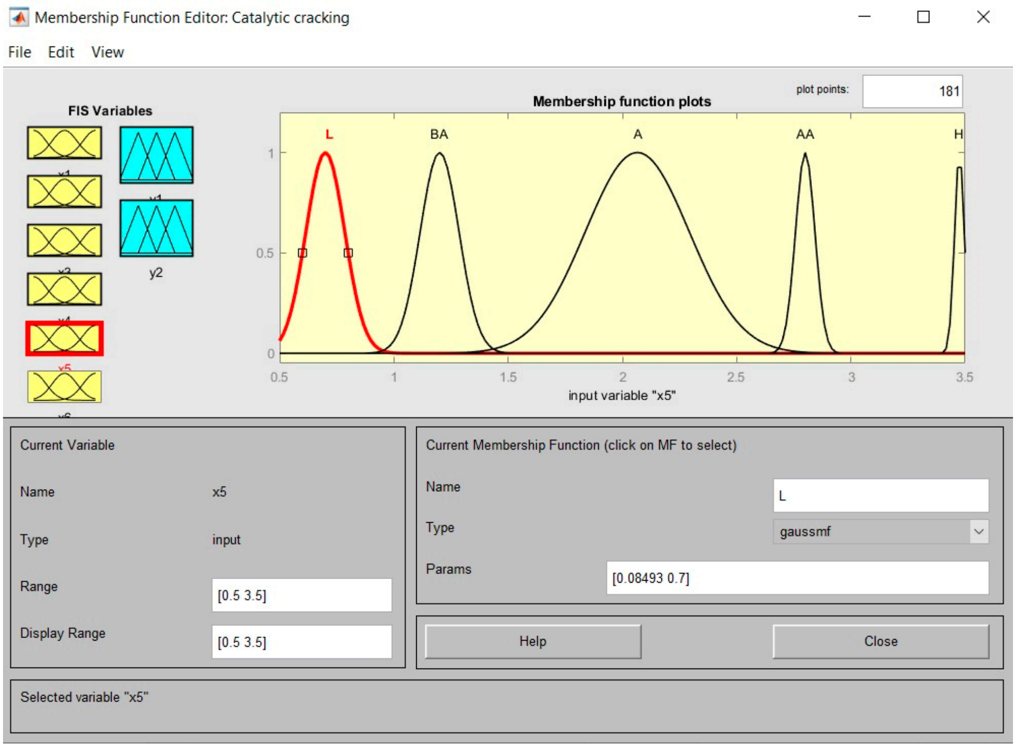

Figure 7. Reactor pressure membership function.

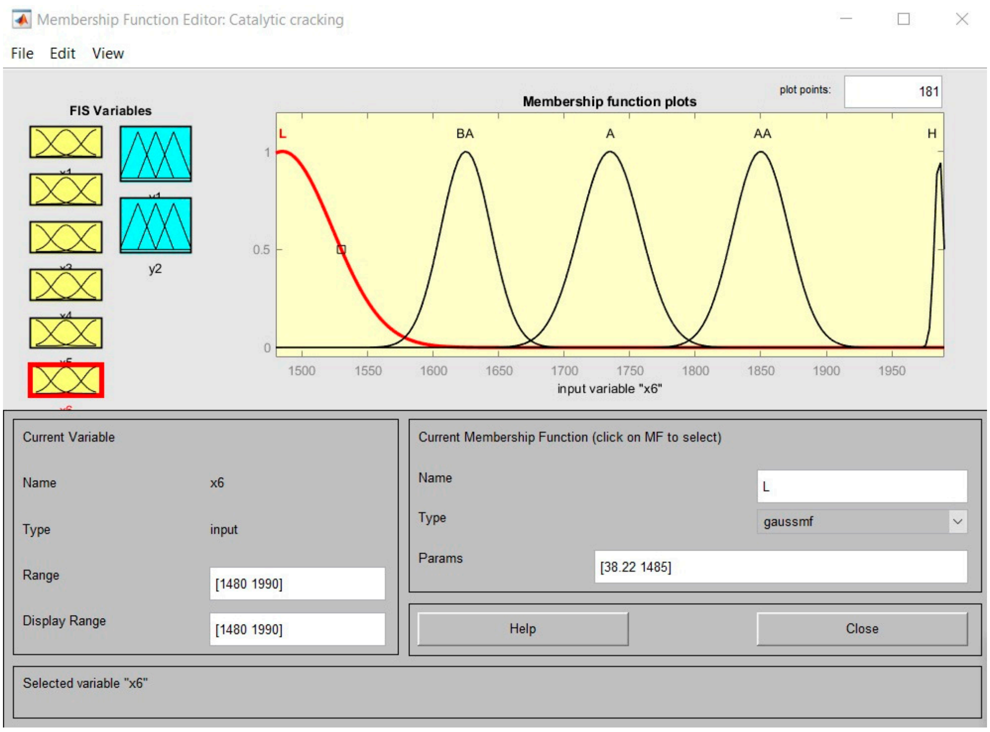

Figure 8. Catalyst consumption membership function.

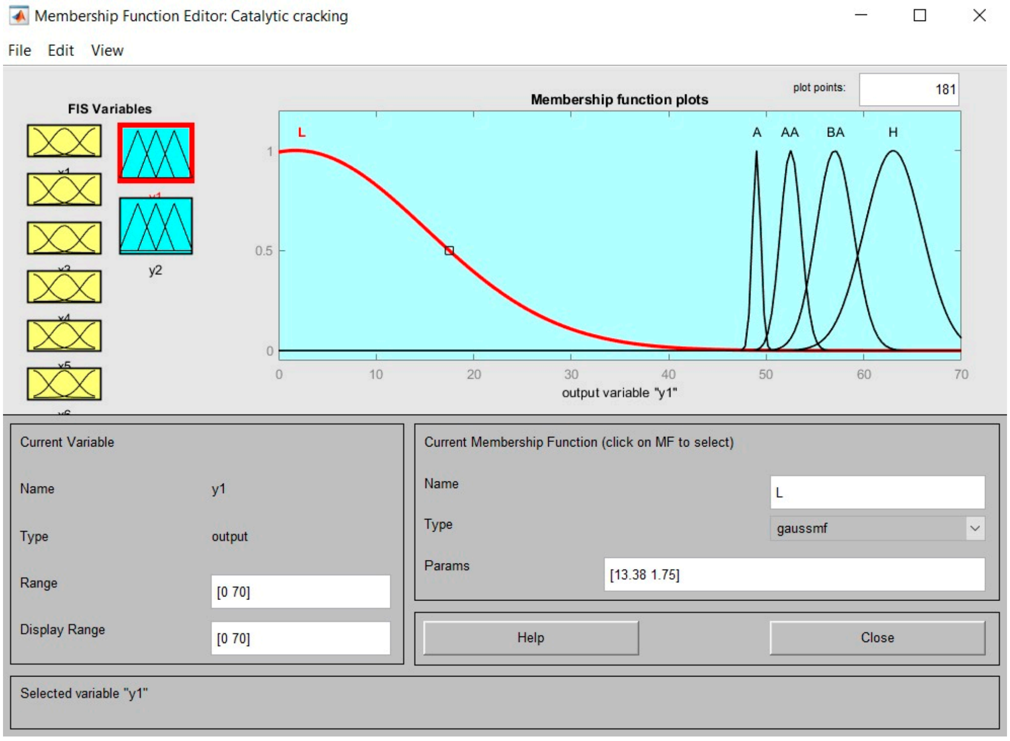

Figure 9. Gasoline yield membership function.

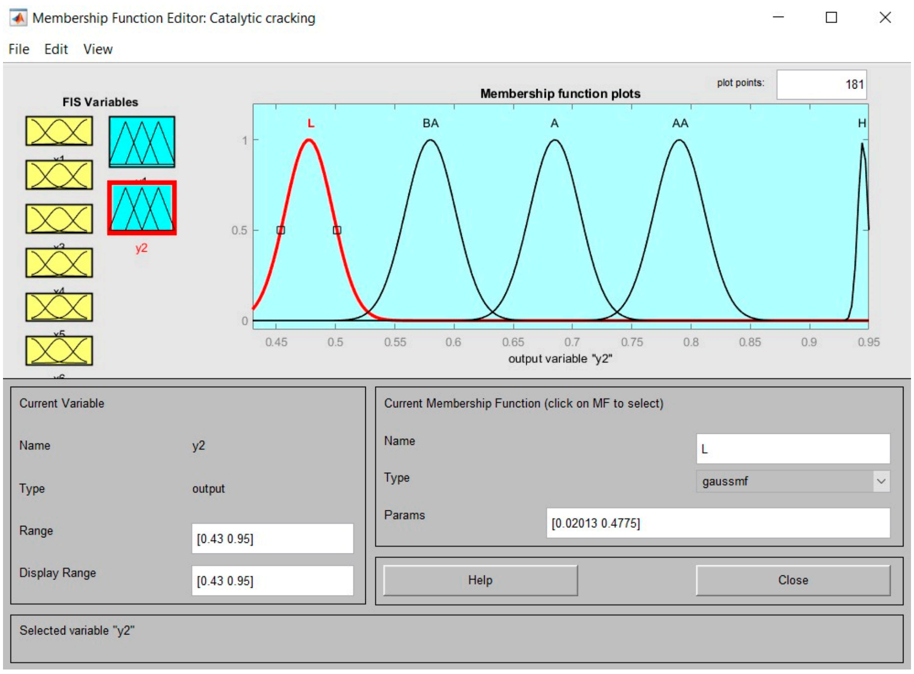

Figure 10. Gasoline density membership function.

The graph in Figure 3 shows the Gaussian membership function for the input variable x_1 (raw material consumption) with a range of values from 0 to 400. The graph in Figure 4 shows the Gaussian membership function for the input variable x_2 (raw material density) with a range of values from 0.4 to 1.6. The graph in Figure 5 shows the membership function for variable x_3 (raw material temperature) with a range of values from 0 to 255. The graph in Figure 6 shows the membership function for input variable x_4 (reactor temperature) with a range of values from 0 to 600. The graph in Figure 7 shows the membership function for the input variable x_5 (reactor pressure) with a range of values from 0.5 to 3.5. The graph in Figure 8 shows the membership function for the input variable x_6 (catalyst consumption) with a range of values from 1480 to 1990. The graph in Figure 9 shows the membership function for the output parameter y_1 (gasoline yield) with a range of values from 0 to 70. The graph in Figure 10 shows the membership function for the output parameter y_2 (gasoline density) with a range of values from 0.635 to 0.735. Using membership functions and rules, the system can predict the output values y_1 and y_2 based on the input variables $x_1 - x_6$. Thus, fuzzy logic rules establish relationships between raw material consumption (Figure 3), density (Figure 4), raw material temperature (Figure 5), temperature in the reactor (Figure 6), pressure in the reactor (Figure 7), and catalyst consumption (Figure 8), and their influence on both gasoline yield (Figure 9) and density (Figure 10). Below in Figure 11 are the results of creating rules in the Fuzzy Logic Toolbox environment.

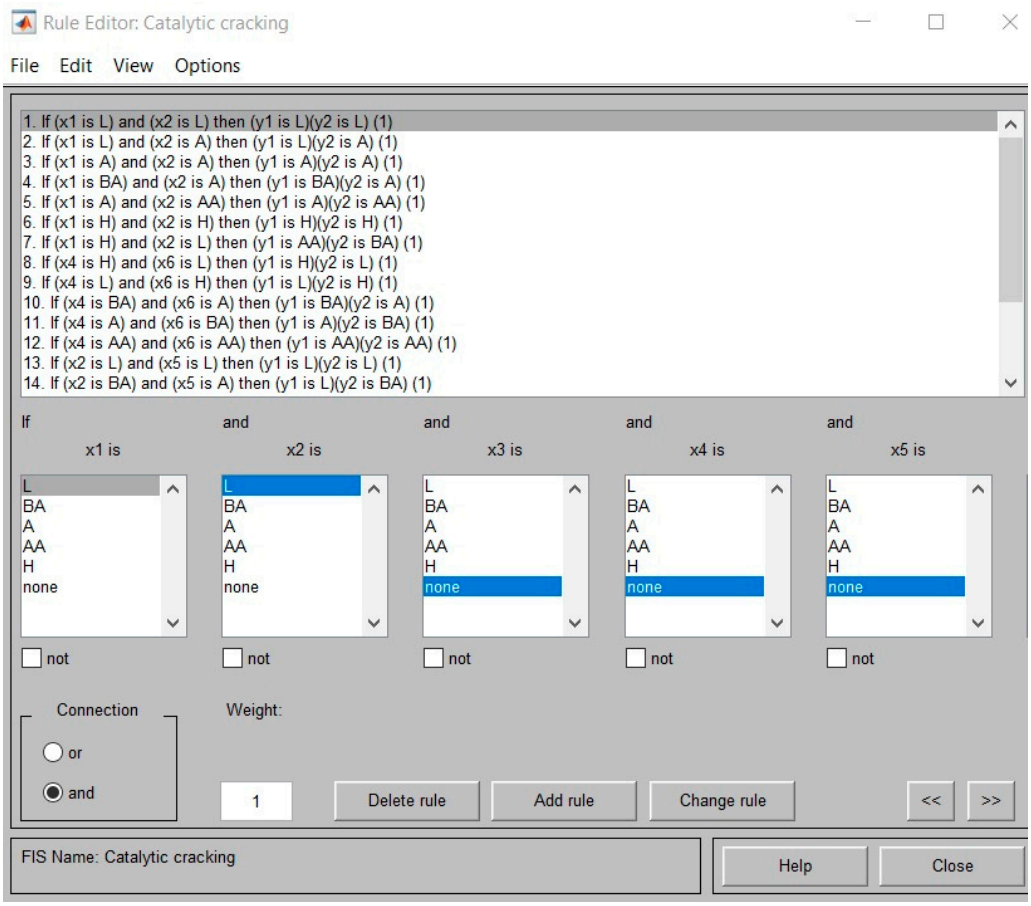

Figure 11. Rules editor in the Fuzzy Logic Toolbox environment.

In fuzzy control the emphasis is on the use of rules, while in conventional control this level of emphasis is on ordinary differential equations (Figure 11). Using linguistic rules rather than a mathematical system is more natural to human cognition. In a fuzzy rule, the rules are always true, but at different levels, from zero to one. The inference system first checks whether the rule premises are valid for the current case.

The defuzzification interface maps the outputs of the inference engine to obtain control action. For this purpose, it uses membership functions similar to those used by a fuzzifier. The two most important and widely used fuzzy inference methods are the Mamdani method and the Sugeno method. The main difference between these methods lies in the consequences of fuzzy logic rules. Mamdani-type fuzzy inference methods use fuzzy sets as consequences of rules, while Sugeno-type systems use linear functions [39]. In this study, the Mamdani inference algorithm is selected to interpret the rules and generate the output.

Figures 12 and 13 show interfaces displaying the rule base browser in the MATLAB environment and the dependence of the yield and density of gasoline on the input parameters.

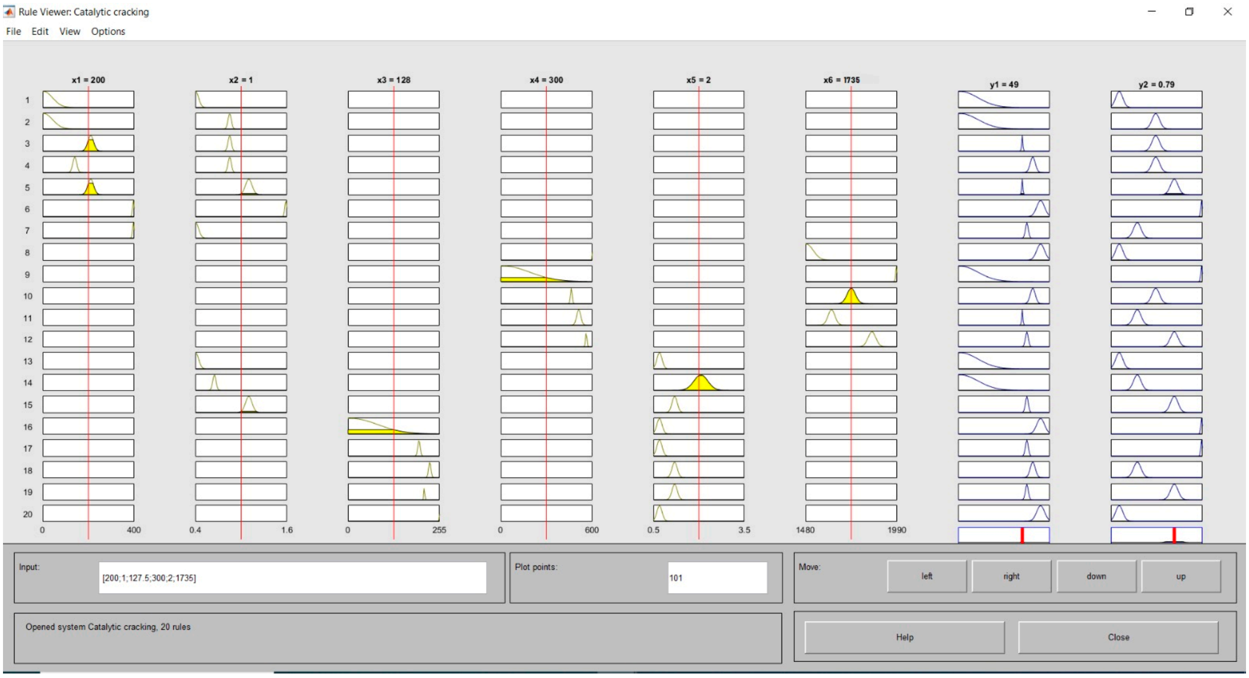

Figure 12. Rules browser in the MATLAB environment.

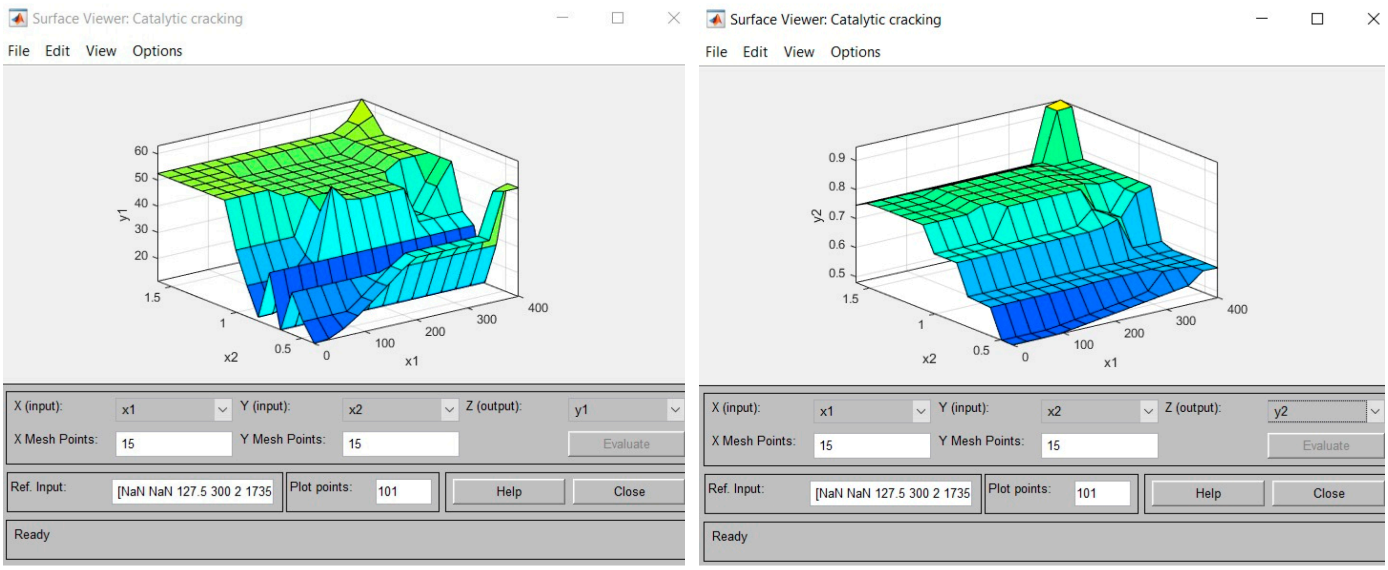

Figure 13. Dependence of gasoline yield and density on input parameters.

Based on surface graphs (Figure 13) and rules, it can be concluded how input variables affect output variables and are consistent with the rule base formed above. If the premises satisfy the requirements, these rules are selected. This step is also known as "Compliance". The inference system makes decisions afterward.

The results of the considered method indicate the possibility of its use for formalizing data and using it in the synthesis of a control algorithm for a reactor–regenerator block, for example, based on a fuzzy production model. With such a formalization of data, it is advisable to choose the number of terms from a series of odd natural numbers, starting from three, since the central term corresponds to the normal operating mode of the technological process, and neighboring terms correspond to deviations from it. The more terms, the more accurately you can react (control) to changes in process parameters. However, this leads to an increase in logical production rules when controlling the process, which reduces its reliability during implementation.

The main reasons for choosing fuzzy learning in the presented work are as follows: the fuzzy nature of the input operating and output parameters of the object under study, described on the basis of the knowledge, experience, and intuition of the decision maker and subject area experts; the presence of experienced decision makers and experts who make effective decisions for managing the operating modes of the object under study—the catalytic cracking unit at the Shymkent oil refinery; and the ability to build, based on the collected fuzzy information, considerations, and conclusions, a rule base that effectively and quite adequately describes the process of obtaining high-quality gasoline.

4. Discussion

The developed method for synthesizing linguistic models is based on the mathematical apparatus of fuzzy set theories, logical rules of conditional inference, and the use of the experience, knowledge, and intuitions of a group of experts. When developing a fuzzy production model of the reactor–regenerator block of a catalytic cracking unit, the most informative parameters that characterize the quality of the process were found. Additionally, by changing the parameters, the process is controlled to produce gasoline in the required quantity. Using the rules browser, the progress of fuzzy inference can be tracked for each rule and the defuzzification procedure can be executed (Figure 12).

The rules browser interface displays all the rules involved in the system. This allows us to see which rules are triggered under the current input values and visualizes the degree of activity of each rule. The degree of activation of each rule is displayed as a graph or numeric value that shows how much each rule affects the output values y_1 and y_2. Based on the activated rules and their activation degrees, the rule browser calculates a fuzzy output value of y_1 and y_2, which is then defuzzified to produce a crisp value. This allows us to effectively tune and optimize the system to achieve the desired results in the catalytic cracking process. Many combinations of antecedents and consequences are presented for clarity in the form of a graph in three-dimensional space (Figure 13). A surface graph shows the dependence of the output variables y_1 and y_2 on the input variables x_1 and x_2. A color gradation from blue to green and yellow indicates the heights of y_1 and y_2. For certain values of x_1 and x_2, the output of y_1 reaches its maximum value (yellow area). The same surface graphs were obtained for other process input parameters—x_3—x_6; the dependence of outputs y_1 and y_2 on input parameters x_1–x_6 was analyzed.

According to the results of the analysis and the comparison of the results in the rules browser, if the temperature in the reactor is lower than the set one, despite the large quantity of raw materials used and catalyst consumption, the gasoline yield decreases. A qualitative indicator—the density of gasoline—is more dependent on the density and temperature of the raw materials used, and the pressure in the reactor. The lower the density of gasoline, the higher the quality of gasoline is considered. The linguistic models developed through the method of synthesis of linguistic models make it possible to select the optimal operating mode of the unit, which makes it possible to control the catalytic cracking process and obtain the desired product yield in the required quality.

The restrictions of the developed models also include the need to improve their performance in terms of ease of use and efficiency in obtaining results with the necessary adequacy, for example, rule base optimization by introducing their weighting coefficients and priorities, as well as removing unimportant overlapping rules, etc. This can lead to increased adequacy and ease of use. Improvement can be achieved through the use of more complex rule algorithms for processing fuzzy data and synthesizing linguistic models, for example, to illustrate the real-life conditions in which the model is used, considering the operating scenario of a catalytic cracking unit at the Shymkent oil refinery.

This article presents the main process parameters used for modeling. Figures 3–10 show the dependence of the output parameters on the input operating parameters. These data were obtained through on-site experiments and analysis of actual production conditions. These examples and data demonstrate how the model responds to changes in input parameters and help better to understand its behavior in real-world production environments. To improve the adequacy of the model, experiments can be conducted by adding additional input parameters, creating additional rules, and comparing the values of the output parameters. At the same time, it is necessary to ensure the speed of obtaining results, i.e., the performance of the models. This is usually achieved by minimizing the number of rules in the database and their ease of use. It is also possible to improve the performance of the model by introducing additional data sources, such as data on the state of equipment, the chemical composition of raw materials and catalyst, and external conditions. Adding additional parameters can improve the accuracy of models.

Thus, to solve problems of increasing the performance of the proposed models, in fact, it is necessary to formalize and solve decision-making problems that provide the best compromise solution that ensures high adequacy and performance of the models.

Even though the proposed approach to controlling the catalytic cracking process based on developed linguistic models and on the use of a fuzzy model is acceptable, from the point of view of their practical implementation, it has some limitations. As the results of the study showed, the catalytic cracking process is carried out under conditions of frequently changing disturbances from the qualitative characteristics of the raw materials, as well as the practical uncontrolled adequacy of the catalyst. The available information on the composition of the raw materials used, in the form of individual points of the fractional composition, carries very superficial information about the chemical composition of the raw materials.

The main restriction of the proposed approach is that, from the technical perspective, it is quite difficult to construct a rule using several input or output parameters simultaneously. Also, the correctness of the constructed model depends on the knowledge and experience of subject area experts who participate in the survey as part of the study. To address these issues in future research, the authors plan to use the methodology of system research, decomposition, and improvement of the method of conducting expert assessment and processing the results obtained to increase the adequacy of the developed models.

5. Conclusions

As a result of the study, the input, output, intermediate, and control parameters of the unit for catalytic cracking of petroleum fractions and cracking of vacuum gas oil in a moving catalyst bed were determined. A method for synthesizing linguistic models of fuzzy systems was developed, based on the use of expert assessment methods and the mathematical apparatus of fuzzy set theories. Using the proposed method, linguistic models were developed and catalytic cracking processes were simulated. Using the results of mathematical modeling, the rule base was adjusted and the performance of the control approach was assessed when introducing external disturbances from changes in the composition of the raw material, accompanied by changes in the pressure and temperature of the reactor in the reactor–regenerator block of the catalytic cracking unit. The ranges and norms of term values were obtained based on the production data of the Shymkent oil refinery with an additional survey of several experts from this plant. The use of tools of the Fuzzy Logic Toolbox package can significantly reduce the time spent on fuzzy modeling, reduce the number of possible errors, and reduce the labor intensity of developing a fuzzy model.

The presented approaches were implemented by creating mathematical models and solving problems related to the selection of optimal operating modes of the reactor–regenerator block of a catalytic cracking unit used for the production of high-octane gasoline in a fuzzy environment.

The proposed model for the synthesis of linguistic models in a fuzzy environment solves the problem of a shortage of initial information by integrating expert knowledge and applying fuzzy logic. This approach allows effective modeling and control of the catalytic cracking process under conditions of uncertainty and initial data fuzziness.

The results of the study are considered theoretically promising, expanding the boundaries of practical problems to be solved for modeling, optimization, and control of chemical technological systems, and making it possible to model and control the operating modes of a complex chemical and engineering system, taking into account the multiple criteria and fuzziness of the initial information.

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Data Availability Statement: Data supporting the results of this study were obtained from the Shymkent Oil Refinery, but restrictions apply to the availability of these data, which were used under license for the current study, and are therefore not publicly available. However, the data are available from the authors upon reasonable request and with the permission of a third party (Shymkent Refinery). To request data from this study in the future, you can contact the author by correspondence: Narkez Boranbayeva, ades_98@mail.ru.

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