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Methods for Modeling and Optimizing the Delayed Coking Process in a Fuzzy Environment

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Abstract: Technological objects and processes are often characterized by fuzzy initial information necessary for developing their models and optimization. The purpose of the study is to develop a method for synthesizing linguistic models of fuzzy described objects and a heuristic method for solving the multicriteria optimization problem in a fuzzy environment. Based on the expert assessments and logical rules of conditional inference, a method for synthesizing linguistic models was developed for describing processes with fuzzy input and output parameters. To solve the problem of multicriteria optimization, a heuristic method based on the modification and combination of various optimality principles is proposed. Coking reactor models were developed by modifying the successive regression inclusion method and the least squares method. Linguistic models of the delayed coking process were developed in the Fuzzy Logic Toolbox, allowing to evaluate the coke quality depending on the temperature and pressure of coking reactors. Using the proposed heuristic method, the problem of two-criteria optimization of the delayed coking process with fuzzy constraints is solved. The results confirm the advantages of the proposed fuzzy approach compared with the well-known approaches. Unlike them, the proposed method allows making adequate decisions in a fuzzy environment by maximizing the use of available fuzzy information.

Keywords: chemical-technological system; decision maker; delayed coking unit; linguistic model; petroleum coke

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1. Introduction

The technological processes of processing raw materials and manufacturing products in oil refining, petrochemicals, and other industries proceed in chemical-technological systems (CTS) [1,2]. These CTS include a delayed coking unit (DCU) designed for deep processing of tar or fuel oil in order to obtain high-quality petroleum coke from them and consisting of interconnected reactors, columns, furnaces, and other units [3]. Petroleum coke is used in the production of electrodes and anodes, is used in space technology and electronics, and is a valuable raw material for metallurgy [4].

DCU of the Atyrau Refinery is characterized by the fuzziness of some parameters and indicators of coke quality (volatility and ash content), which are not determined by measuring instruments under production conditions. In practice, such indicators are evaluated by the decision maker (DM), production manager, and experts in natural language in the form of fuzzy verbal information. All this makes it difficult to develop mathematical models of DCU units, determine the quality of the produced coke, and optimize the delayed coking process using traditional methods. In this regard, the tasks of developing models and optimizing the process of delayed coking in a fuzzy environment are becoming very urgent for the science and practice of oil refining and for consumers of high-quality petroleum coke. In this regard, the tasks of developing models and optimizing the process of delayed coking in a fuzzy environment are becoming very urgent tasks of science and practice in oil refining and motivate this study.

To conduct the process of delayed coking in DCU coking reactors in the optimal mode, it is necessary to develop models that describe the dependence of the volume, quality indicators of coke on the input, and operating parameters, taking into account the fuzziness of the initial information [5]. Some important indicators, quality indicators of petroleum coke produced at the DCU, due to the complexity or impossibility of measuring them in a production environment, are not clearly assessed by DM, experts based on their experience, knowledge, and intuition, i.e., intelligence. This complicates the development of mathematical models for determining such fuzzy parameters of CTS using traditional methods [6–8]. In this regard, for the development CTS models and processes in a fuzzy environment, it is required to develop special methods that can overcome the problems of uncertainty due to the fuzziness of the information available.

To automate the process of optimizing the delayed coking process in a fuzzy environment according to the selected criteria, it is required to develop a heuristic method for multicriteria optimization of reactor operating modes based on mathematical models and using the experience, knowledge, and intuition of DM [5]. All these conditions and the need to develop models of coking reactors and optimize the delayed coking process, which is characterized by fuzzy initial information, were the motivations for developing methods for synthesizing linguistic models and multicriteria optimization of the process under study in a fuzzy environment.

A well-known approach to solving problems of uncertainty arising due to the random nature of the initial data is the use of probabilistic methods based on probability theory and mathematical statistics [9,10]. But it should be noted that these methods are applicable only under conditions when the axioms of probability theory are fulfilled, for example, the static stability of an object and repeated experiments under the same conditions. In practice, these conditions are often not met, which leads to the illegality of the use of probabilistic methods, and the cause of uncertainty is the fuzziness of the initial information. Often, even with the theoretical possibility of measuring some parameters, in practice, their measurement may turn out to be inefficient or economically unjustified, and it is better to estimate them as fuzzy.

In production conditions, such difficult-to-quantify CTS are quite effectively managed by DM and experienced technologists based on their knowledge, experience, and intuition, which are not clearly expressed [11]. Therefore, solving the problem of developing models and crisp operating modes of fuzzy CTS based on fuzzy information became the motivation for developing methods for synthesizing linguistic CTS models and heuristic approaches to solving the problem of studying them in fuzzy work. The method of synthesizing linguistic models and the heuristic approach to solving a multicriteria problem in a fuzzy environment, proposed in this paper, are based on the use and variants of the methods of theories of fuzzy multiple and expert assessments [5,6,11–14]. Many CTS have experienced DMs who are subject matter experts. By properly organizing the process of interviewing these experts and formalizing the obtained fuzzy information on its basis, it is possible to develop models that take into account all the complex relationships among various parameters of the CTS under study. The resulting models based on fuzzy information can be more meaningful than models developed by traditional methods and can more adequately describe real production systems and tasks in a fuzzy environment.

The difference between the results of this study compared to the known results on the topic under study is that the models of complex, fuzzy CTS-DCU are developed on the basis of a systematic approach [15,16], using the proposed linguistic method for synthesizing models in a fuzzy environment. Based on the developed models and the proposed heuristic method, the operating modes of DCU coking reactors are optimized under conditions of multicriteria and fuzzy initial information.

As a result of the analysis of various methods for developing mathematical models and optimizing complex CTS, it was revealed that research papers do not cover the development of linguistic CTS models and optimizing their modes of operation according to the vector of criteria. In the works [6,11,17–20], the approaches to the development of mathematical models and optimization of the parameters of technological objects, which are characterized by the fuzziness of the initial information, are investigated and proposed. In these and other analyzed works on modeling and optimization of complex objects, the issues of developing linguistic models with fuzzy input and output parameters of the object have not been studied. In addition, in the well-known methods for solving fuzzy optimization problems, at the stage of formulation, the fuzzy problem is converted to a set of crisp problems and then solved by existing methods [21,22]. 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 obtained solutions to reality.

The novelty of the proposed fuzzy approach to modeling and optimization of complex, fuzzy CTS lies in following:

- the proposed method of synthesizing linguistic models allows developing effective CTS models in conditions of fuzzy input and output parameters, when other known methods are not effective or not applicable;
- the proposed heuristic method of multicriteria optimization, in contrast to the known methods for solving fuzzy problems, solves the original fuzzy problem without converting it to crisp ones in a fuzzy environment. This allows, due to the maximum use of the collected fuzzy information (knowledge, experience, intuition of DM, experts), to make effective and adequate decisions in a fuzzy environment.

This study is devoted to the development of a method for synthesizing linguistic models of the CTS unit and a heuristic method for optimizing its operating modes in a fuzzy environment. The proposed methods allow, due to a systematic approach that uses the methods of fuzzy set theory and expert assessment in a complex way, to solve the indicated gaps in existing modeling and optimization methods.

2. Problem Statement

The investigated DCU, like many CTSs, is characterized by fuzzy initial information about the quality of the produced petroleum coke, which is necessary for developing models and optimizing the delayed coking process. Under these conditions, it is necessary to develop DCU models and optimize the delayed coking process in a fuzzy environment, based on the experience, knowledge, and intuition of DM experts [4].

In this regard, the purpose of this work is to develop a method for synthesizing linguistic models of DCU-type fuzzy systems, formalization, formulation of the problem of multi-criteria choice of the optimal operating mode of an object in a fuzzy environment, and development of a heuristic method for solving it.

The proposed method for the synthesis of linguistic models, with fuzzy input and output CTS parameters, is based on the methods of expert assessments and the fuzzy conditional inference rule [11,12]. In addition, with crisp input, regime parameters, and fuzzy CTS output parameters, which can also take place in practice, models are developed based on a modification of the method of sequential inclusion of regressors and the least squares method.

To formalize and mathematically formulate the problem of multicriteria optimization in a fuzzy environment with conflicting criteria, i.e., decision-making problems, various principles of optimality are modified and combined [5]. The proposed method for solving the formulated decision-making problem in a fuzzy environment will be heuristic and, based on the experience, knowledge, and intuition of DM and models, allows choosing the best solution in a fuzzy environment using a computer system.

3. Object, Materials and Methods

The object of the study is the Delayed Coking 21-10/6, Atyrau Refinery, which is characterized by the fuzziness of some of the initial information. The prospect of the delayed coking process at the DCU is substantiated by the following factors: adaptability of the process to the processing of various raw materials (fuel oil, tar, and other oil refining residues); high performance of the DCU (105 t/h for raw materials); and the ability to select the optimal operating mode of the installation using computer systems [23].

Figure 1 shows the flow diagram of DCU 21–10/6, in which the technological process of delayed coking takes place, and shows the connections between the main units of the installation [3]. The raw material of the studied DCU is tar, and the target product is petroleum coke.

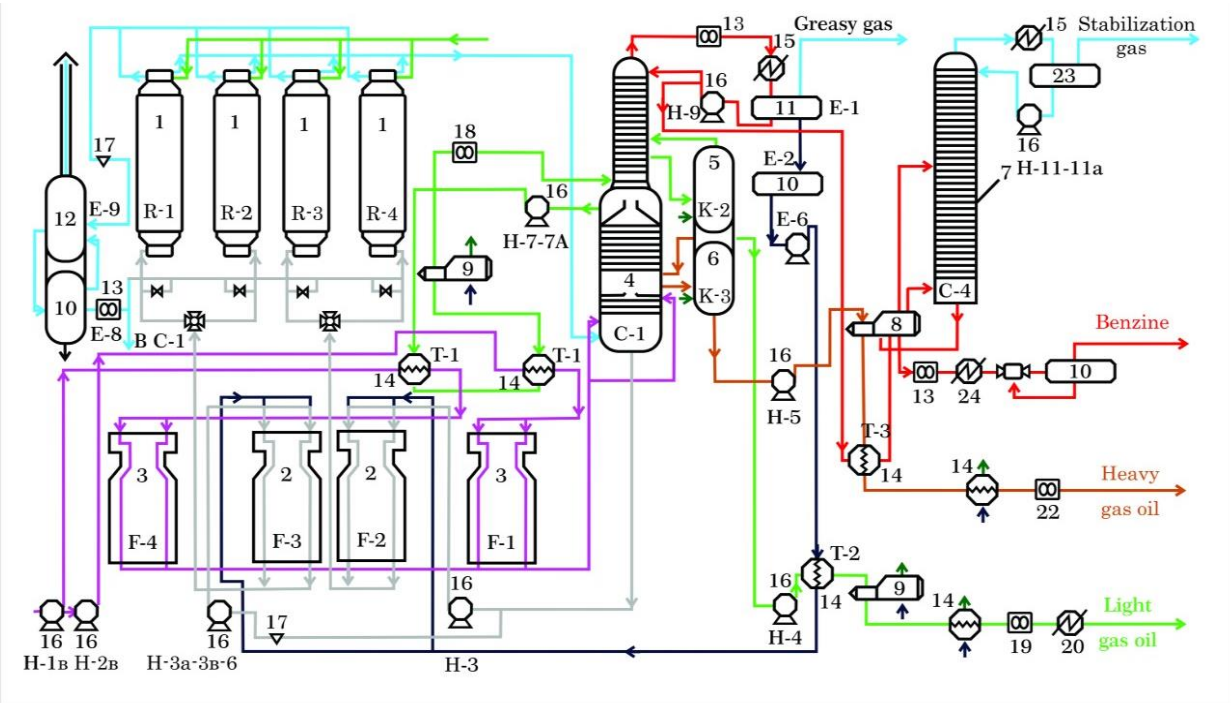

Figure 1. Technological scheme of the DCU 21–10/6. The main units of the DCU are as follows: 1—coking reactors; 2—secondary raw material heating furnaces; 3—primary raw material heating furnaces; 4—the main rectification column.

The technological process at the DCU proceeds as follows. Coking primary raw materials through the furnaces (F-1, F-4), after heating to the required temperature, is fed into the main distillation column C-1. In distillation column C-1, heated raw materials and vapors of oil products from coking reactors (R-1-R-4) are separated into different fractions depending on the boiling point (gas, gasoline, light and heavy gas oils, and residues). Gasoline, light and heavy gas oils from column C-1 are commercial products; the gas is used as internal fuel, and the residues are heated to the required temperature in furnaces of secondary raw materials (F-2, F-3) and sent to coking reactors R-1–R-4. In the coking reactors, the target product is produced: petroleum coke and the resulting vapors of petroleum products for separation into fractions are returned to the distillation column C-1.

The volume and quality indicators of coke and other DCU products (gasoline, light, and heavy gas oils) depend on the process conditions, and the value of the input and operating parameters, i.e., from the operating modes of the installation. To select the optimal operating mode of the DCU coking reactors, which provides the maximum volume of coke with high-quality indicators, it is necessary to develop mathematical models that describe the dependence of the volume and quality of coke on the input, operating parameters of the coking reactors [24]. Since the qualitative indicators of coke are estimated as fuzzy with the participation of DM and experts, it will be necessary to synthesize linguistic models based on fuzzy input and output parameters of the coking process.

To solve the problems of modeling and optimizing the operating modes of fuzzy coke chambers, it is necessary to solve the following problems:

- To develop a method for synthesizing linguistic models of technological processes with fuzzy input and output parameters. Based on the developed method for the synthesis of linguistic models, synthesize linguistic models and conduct fuzzy modeling of the coking process in coke reactors to assess the quality of the produced coke;
- to develop a heuristic method for multicriteria optimization of the operating mode of coking reactors to maximize the volume of coke produced with the best quality indicators. Application of the proposed heuristic method to optimize the coking process and comparison of the obtained results with the results of known methods.

3.1. Linguistic Model Synthesis Method

A block diagram of the developed method for synthesizing linguistic models based on fuzzy input and output parameters of the object is shown in Figure 2.

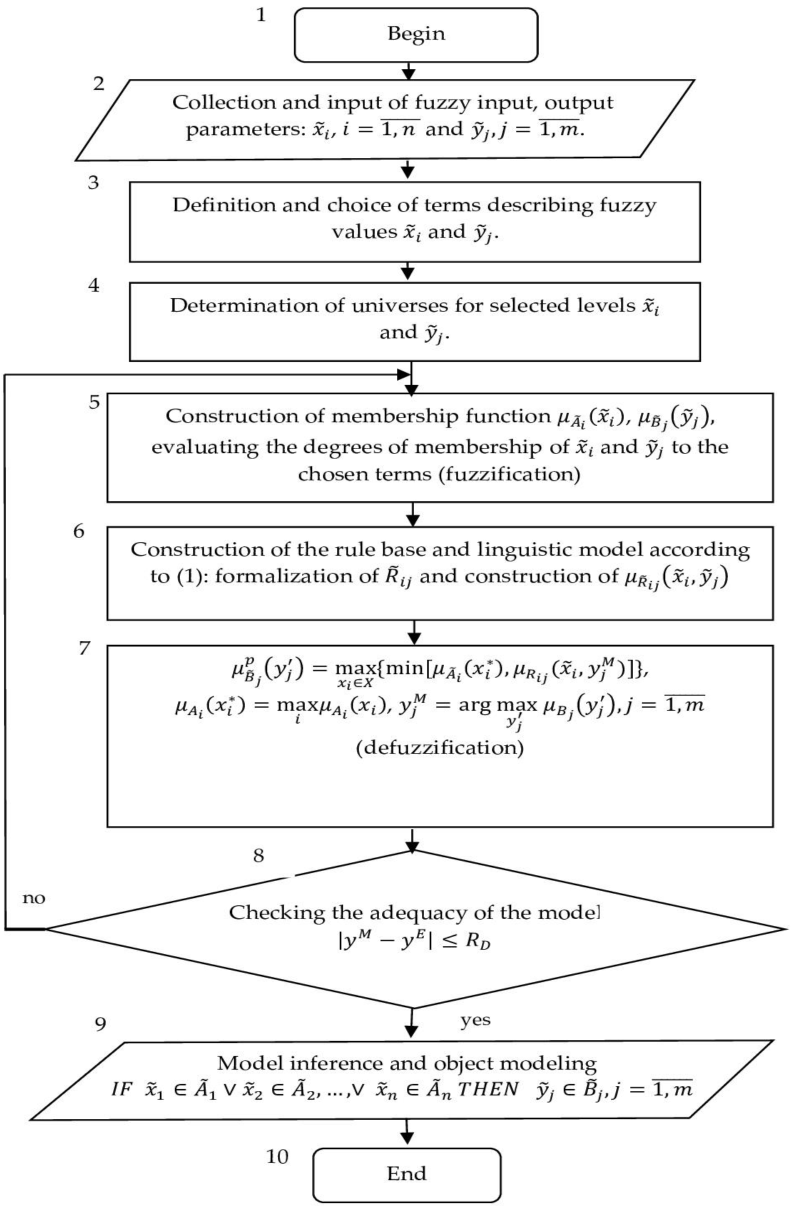

Figure 2. Block diagram of the linguistic model synthesis method.

Let us give a detailed description of the main blocks of the proposed method for the synthesis of linguistic models. In block 2, fuzzy input and operating parameters of the process $\widetilde{x}_i$, $i = \overline{1,n}$ are selected, affecting 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 chosen levels $\widetilde{x}_i$ and $\widetilde{y}_j$ are defined. At the same time, terms (fuzzy set) are fuzzy descriptions of the values of the corresponding levels of parameters, and universes are intervals of their numerical mapping.

In block 5, the fuzzification procedure is implemented, i.e., membership functions are constructed that describe the degree of membership in fuzzy sets (terms). In this case, it is recommended to construct membership functions using the Fuzzy Logic Toolbox application of the MATLAB system [25,26].

In block 6, a rule base and linguistic models are created, consisting of logical rules of conditional inference, which have the following structure:

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

Linguistic models verbally describe the influence of fuzzy input parameters $\widetilde{x}_i$, $i = \overline{1,n}$ on fuzzy output parameters $\widetilde{y}_j$, $j = \overline{1,m}$ and are synthesized on the basis of a rule base, which is determined on the basis of expert evaluation methods and fuzzy set theories. For convenience, the rule base can be arranged in the form of a table, in which, using term sets (selected in block 3), fuzzy values of input, regime parameters $\widetilde{x}_i$ and the corresponding fuzzy values of output parameters $\widetilde{y}_j$ are given. On the basis of this table, it is possible to formalize fuzzy mappings $\widetilde{R}_{ij}$, which make it possible to determine the relationship between linguistic parameters $\widetilde{x}_i$ and $\widetilde{y}_j$.

For a t 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 $\mu_{\widetilde{R}_{ij}}(\widetilde{x}_i, \widetilde{y}_j)$ on the basis of the membership functions of the fuzzy mapping $\widetilde{R}_{ij}$. In the general case, such a matrix for a level p term has the form:

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

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

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

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

Based on this rule, you can determine the values of the membership function of the output parameters using the formula:

$$\mu^t_{\widetilde{B}_j}\left(y'_j\right) = \max_{x_i \in X}\left\{\min\left[\mu_{\widetilde{A}_i}(x_i^*), \mu_{R_{ij}}\left(\widetilde{x}_i, y_j^M\right)\right]\right\} \tag{2}$$

In Formula (2) through x_i^*—fuzzy values of operating parameters estimated by experts are designated. Then, the desired set, to which the current values of the operating parameters belong, is defined by the formula $\mu_{A_i}(x_i^*) = \max_i \mu_{A_i}(x_i)$, i.e., as a set in which the values of the operating parameters have the maximum value of the membership function.

To defuzzify results, i.e., to determine the numerical values of the output parameters y_j^M from the set of fuzzy decisions, you can use the following expression: $y_j^M = \arg\max_{y'_j} \mu_{B_j}\left(y'_j\right)$, $j = \overline{1,m}$. Thus, the numerical values of the output parameters are chosen as the argument of 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 a sharp form of the membership function in the region of the maximum value. If the graph of the membership function is flatter, i.e., in the region of the maximum value, with many points close in value, then as the numerical values of the output parameter y_j^M you can choose their average value.

To determine the volume of coke and its quality indicators based on the modification of the method of sequential inclusion of regressors [27], fuzzy regression models were developed, and their parameters were identified using the REGRESS program [28], which implements the least squares method [29].

3.2. MC + PO Method

In general, the problem of multicriteria optimization of the coking process in a fuzzy environment based on the modification of the principles of the main criterion (MC) and Pareto optimality (PO) is written as:

$$\max_{\mathbf{x}\in X}\mu_0^1(\mathbf{x}),$$

$$X=\left\{\mathbf{x}:\mathbf{x}\in\Omega\wedge\arg\left(\mu_0^i(\mathbf{x})\geq\mu_R^i\right)\wedge\ \underset{\mathbf{x}\in\Omega}{\operatorname{argmax}}\sum_{q=1}^{L}\boldsymbol{\beta}_q\mu_q(\mathbf{x})\wedge\sum_{q=1}^{L}\boldsymbol{\beta}_q=1\wedge\boldsymbol{\beta}_q\geq 0,\ i=\overline{2,m},q=\overline{1,L}\right\},$$

where $\mu_0^1(\mathbf{x})$—normalized main criterion; $\mathbf{x}=(x_1,\ldots,x_n)$—vector of input, mode parameters of DCU objects; Ω —area of definition of the vector $\mathbf{x}$; $\wedge$—logical "and", requiring the truth of all expressions connected through them; $\mu_0^i(\mathbf{x})$ и $\mu_R^i, i=\overline{2,m}$—local criteria, except for the main criterion and their specified DM boundary values; $\boldsymbol{\beta}_q,\ q=\overline{1,L}$—weight coefficients of fuzzy constraints; $\mu_q(\mathbf{x})$—membership functions that estimate the degree of fulfillment of fuzzy constraints.

To solve the stated problem of multicriteria optimization with m criteria and L fuzzy constraints based on the principles of MC and PO, a heuristic method MC + PO has been developed, consisting of the following points:

1. For DM, experts determine $p_q, q=\overline{1,L}$—the number of steps for each q-th coordinate of the priority series for the criteria $I_C=\{1,\ldots,m\}$, where 1 is the priority of the main criterion is $\mu_0^1(\mathbf{x})$.
2. To input the values of the vector of weight coefficients $\boldsymbol{\beta}=(\beta_1,\ldots,\beta_L)$, which reflects the mutual importance of fuzzy constraints.
3. To determine the boundary values for local criteria (except for the main—the first one), which are taken into account in the composition of the constraints $\mu_R^i,\ i=\overline{2,m}$.
4. To calculate the lengths of steps $\boldsymbol{h}_q=1/p_q,\ \ q=\overline{1,L}$, to change the coordinates of the vector $\boldsymbol{\beta}=(\beta_1,\ldots,\beta_L)$.
5. By changing the coordinates in the intervals [0, 1] with a step h_q to construct weight vectors $\boldsymbol{\beta}^1,\boldsymbol{\beta}^2,\ldots,\boldsymbol{\beta}^{\mathrm{N}}$, where $N=(p_1+1)\cdot(p_2+1)\cdot\ldots\cdot(p_L+1)$.
6. To determine the term-set for describing fuzzy constraints and construct membership functions that estimate the degree of their fulfillment $\mu_q(\mathbf{x}),\ q=\overline{1,L}$.
7. Using mathematical models of the object, solve the problem of maximizing the main criterion $\mu_0^1(\mathbf{x})$, on an admissible set X, which is determined by the Pareto optimality principle. Identify current solutions: $\mathbf{x}(\mu_R^i,\boldsymbol{\beta})$; $\mu_0^1(\mathbf{x}(\mu_R^i,\boldsymbol{\beta})),\ldots,\mu_0^m(\mathbf{x}(\mu_R^i,\boldsymbol{\beta}))$; $\mu_1(\mathbf{x}(\mu_R^i,\boldsymbol{\beta})),\ldots,\mu_L(\mathbf{x}(\mu_R^i,\boldsymbol{\beta})),\ i=\overline{2,m}$.
8. For DM to analyze the obtained current solutions. If the current solutions satisfy DM, then go to step 9. Otherwise, DM correct the values $\mu_R^i,\ i=\overline{2,m}$ and/or $\boldsymbol{\beta}$ and go to step 3 to improve the solution.
9. The output of the best results selected by the DM: $\mathbf{x}^*(\mu_R^i,\ \boldsymbol{\beta})$, providing the maximum value of the main criterion $\mu_0^1(\mathbf{x}^*(\mu_R^i,\ \boldsymbol{\beta}))$, the values of other criteria $\mu_0^2(x^*(\mu_R^i,\ \boldsymbol{\beta})),\ldots,\mu_0^m(x^*(\mu_R^i,\ \boldsymbol{\beta})),\ i=\overline{2,m}$ and maximum degrees of fulfillment of fuzzy constraints $\mu_1(x^*(\mu_R^i,\ \boldsymbol{\beta})),\ldots,\mu_L(x^*(\mu_R^i,\ \boldsymbol{\beta})),\ i=\overline{2,m}$.

4. Results

4.1. Synthesis of Linguistic Models and Fuzzy Modeling of the Coking Process in Reactors to Assess the Quality of Coke

Based on the method of synthesizing linguistic models proposed in Section 2, linguistic models have been developed that evaluate the quality of coke from R-1–R-4 DCU coking reactors for fuzzy modeling in the Fuzzy Logic Toolbox [25,26].

The main input, operating parameters that most strongly affect the main indicator of coke: $\widetilde{y}_2$—coke volatility based on expert assessment, are chosen: $\widetilde{x}_2$—temperature and $\widetilde{x}_3$—pressure in coking reactors, which are characterized by fuzziness (block 2). The selected fuzzy parameters are described by term sets: $\widetilde{x}_2$ = {"low", "below average", "average", "above average", "high"}; $\widetilde{x}_3$ = {"low", "below normal", "normal", "above normal", "high"}; $\widetilde{y}_2$ = {"very low", "low", "medium", "high", "very high"} (blocks 3.4).

Further, for fuzzification, i.e., for the construction of the membership function of the parameters $\widetilde{x}_2$, $\widetilde{x}_3$ and $\widetilde{y}_2$ the following abbreviated terms are introduced (Table 1).

Table 1. Terms of linguistic variables and their abbreviations for constructing their membership function and forming a rule base.

Terms of Fuzzy Parameters	Symbol
Low	*LW*
Below average	*BA*
Average	*AR*
Above average	*AA*
High	*HG*
Below normal	*BN*
Normal	*NR*
Above normal	*AN*
Very low	*V LW*
Very high	*VHG*

Universes, i.e., universal sets of reduced linguistic variables, necessary for constructing the membership function are shown in Table 2.

Table 2. The universes for fuzzy parameters $\widetilde{x}_2$, $\widetilde{x}_3$, and $\widetilde{y}_2$.

Fuzzy Input Parameters	**Values of Fuzzy Input Variables**				
	LW	*BA, BN*	*AR, NR*	*AA, AN*	*HG*
$\widetilde{x}_2$—temperature at the inlet of coking reactors	470–477	472–479	477–484	482–489	487–494
$\widetilde{x}_3$—pressure in coking reactors	2.4–3.3	3.0–3.7	3.5–4.2	4.0–4.8	4.6–5.5
Fuzzy Output Parameter	**Fuzzy Output Parameter Values**				
	V LW	*LW*	*AR*	*HG*	*VHG*
$\widetilde{y}_2$—volatility of coke	2–5	4–8	7–11	10–14	13–16

Further, the fuzzification procedures and other procedures of the fuzzy inference algorithm are implemented in the Fuzzy Logic Toolbox applications of the MATLAB package. Figure 3a,b shows the membership functions for fuzzy input parameters $\widetilde{x}_2$, $\widetilde{x}_3$, and Figure 4 shows the output parameter $\widetilde{y}_2$, constructed using the Fuzzy Logic Toolbox.

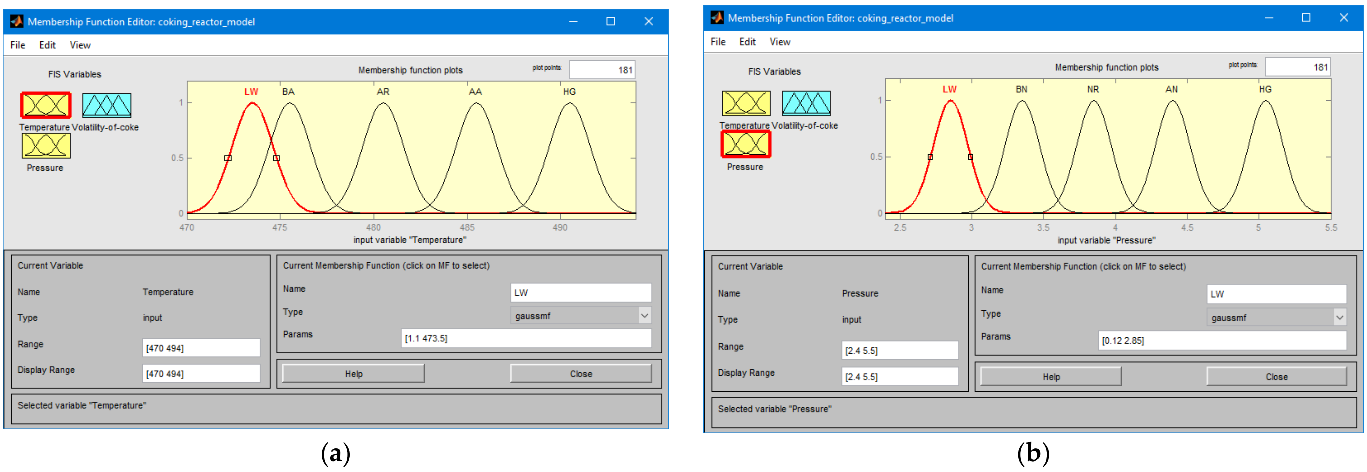

Figure 3. Membership functions of fuzzy input parameters (**a**) $\tilde{x}_2$—temperature; (**b**) $\tilde{x}_3$—pressure in coking reactors.

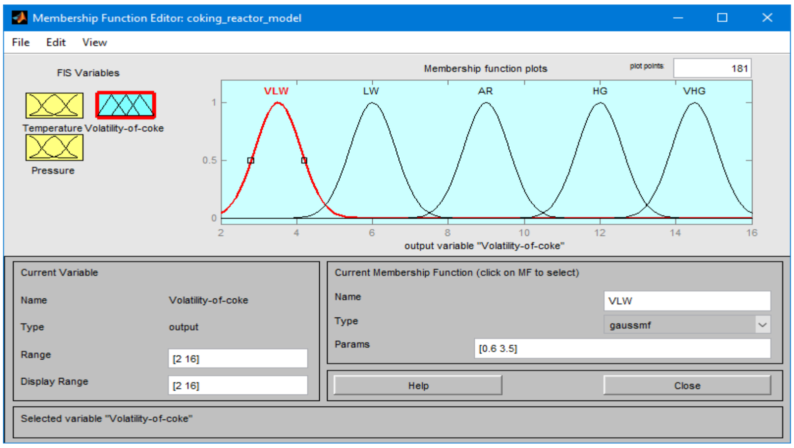

Figure 4. Membership functions of an output parameter $\tilde{y}_2$—volatility of coke.

The developed rule base for the fuzzy inference system, which allows to evaluate the qualities—coke volatility from fuzzy input parameters, is presented below in the form of fuzzy production rules.

$$
\begin{aligned}
&Rule\ 1: \ IF\ «\tilde{x}_2\ is\ LW»\ and\ «\tilde{x}_3\ is\ LW»\ THEN\ «\tilde{y}_2\ is\ VLW»\ F_1;\\
&Rule\ 2: \ IF\ «\tilde{x}_2\ is\ LW»\ and\ «\tilde{x}_3\ is\ BN»\ THEN\ «\tilde{y}_2\ is\ VLW\check{}\ F_2;\\
&Rule\ 3: \ IF\ «\tilde{x}_2\ is\ BA»\ and\ «\tilde{x}_3\ is\ LW»\ THEN\ «\tilde{y}_2\ is\ VLW»\ F_3;\\
&Rule\ 4: \ IF\ «\tilde{x}_2\ is\ BA»\ and\ «\tilde{x}_3\ is\ BN»\ THEN\ «\tilde{y}_2\ is\ VLW»\ F_4;\\
&Rule\ 5: \ IF\ «\tilde{x}_2\ is\ LW»\ and\ «\tilde{x}_3\ is\ NR»\ THEN\ «\tilde{y}_2\ is\ VLW»\ F_5;\\
&Rule\ 6: \ IF\ «\tilde{x}_2\ is\ AR»\ and\ «\tilde{x}_3\ is\ LW»\ THEN\ «\tilde{y}_2\ is\ LW»\ F_6;\\
&Rule\ 7: \ IF\ «\tilde{x}_2\ is\ BA»\ and\ «\tilde{x}_3\ is\ NR»\ THEN\ «\tilde{y}_2\ is\ LW»\ F_7;\\
&Rule\ 8: \ IF\ «\tilde{x}_2\ is\ AR»\ and\ «\tilde{x}_3\ is\ BN»\ THEN\ «\tilde{y}_2\ is\ LW»\ F_8;\\
&Rule\ 9: \ IF\ «\tilde{x}_2\ is\ AR»\ and\ «\tilde{x}_3\ is\ NR»\ THEN\ «\tilde{y}_2\ is\ LW»\ F_9;\\
&Rule\ 10: \ IF\ «\tilde{x}_2\ is\ LW»\ and\ «\tilde{x}_3\ is\ AA»\ THEN\ «\tilde{y}_2\ is\ LW»\ F_{10};\\
&Rule\ 11: \ IF\ «\tilde{x}_2\ is\ AA»\ and\ «\tilde{x}_3\ is\ LW»\ THEN\ «\tilde{y}_2\ is\ AR»\ F_{11};\\
&Rule\ 12: \ IF\ «\tilde{x}_2\ is\ BA»\ and\ «\tilde{x}_3\ is\ AA»\ THEN\ «\tilde{y}_2\ is\ AR»\ F_{12};\\
&Rule\ 13: \ IF\ «\tilde{x}_2\ is\ AA»\ and\ «\tilde{x}_3\ is\ BN»\ THEN\ «\tilde{y}_2\ is\ AR»\ F_{13};\\
&Rule\ 14: \ IF\ «\tilde{x}_2\ is\ AR»\ and\ «\tilde{x}_3\ is\ AA»\ THEN\ «\tilde{y}_2\ is\ AR»\ F_{14};\\
&Rule\ 15: \ IF\ «\tilde{x}_2\ is\ AA»\ and\ «\tilde{x}_3\ is\ NR»\ THEN\ «\tilde{y}_2\ is\ AR»\ F_{15};\\
&Rule\ 16: \ IF\ «\tilde{x}_2\ is\ AA»\ and\ «\tilde{x}_3\ is\ AA»\ THEN\ «\tilde{y}_2\ is\ HG»\ F_{16};\\
&Rule\ 17: \ IF\ «\tilde{x}_2\ is\ LW»\ and\ «\tilde{x}_3\ is\ HG»\ THEN\ «\tilde{y}_2\ is\ HG»\ F_{17};\\
&Rule\ 18: \ IF\ «\tilde{x}_2\ is\ HG»\ and\ «\tilde{x}_3\ is\ LW»\ THEN\ «\tilde{y}_2\ is\ HG»\ F_{18};
\end{aligned}
$$

$$\begin{aligned}
&Rule\ 19: \ IF \ «\tilde{x}_2 \ is \ BA» \ and \ «\tilde{x}_3 \ is \ HG» \ THEN \ «\tilde{y}_2 \ is \ HG» \ F_{19};\\
&Rule\ 20: \ IF \ «\tilde{x}_2 \ is \ HG» \ and \ «\tilde{x}_3 \ is \ BN» \ THEN \ «\tilde{y}_2 \ is \ HG» \ F_{20};\\
&Rule\ 22: \ IF \ «\tilde{x}_2 \ is \ HG» \ and \ «\tilde{x}_3 \ is \ NR» \ THEN \ «\tilde{y}_2 \ is \ VHG» \ F_{22};\\
&Rule\ 23: \ IF \ «\tilde{x}_2 \ is \ AA» \ and \ «\tilde{x}_3 \ is \ HG» \ THEN \ «\tilde{y}_2 \ is \ VHG» \ F_{23};\\
&Rule\ 24: \ IF \ «\tilde{x}_2 \ is \ HG» \ and \ «\tilde{x}_3 \ is \ AA» \ THEN \ «\tilde{y}_2 \ is \ VHG» \ F_{24};\\
&Rule\ 25: \ IF \ «\tilde{x}_2 \ is \ HG» \ and \ «\tilde{x}_3 \ is \ HG» \ THEN \ «\tilde{y}_2 \ is \ VHG» \ F_{25};
\end{aligned}$$

In the above rules, *F1*, … , *F25* are weight coefficients that reflect the degree of confidence in the truth of subconclusions that take values in the range from 0 to 1. In our problem, they are all equal to 1.

The above fuzzy knowledge base is implemented using the FuzzyLogic Toolbox and is shown in Figure 5.

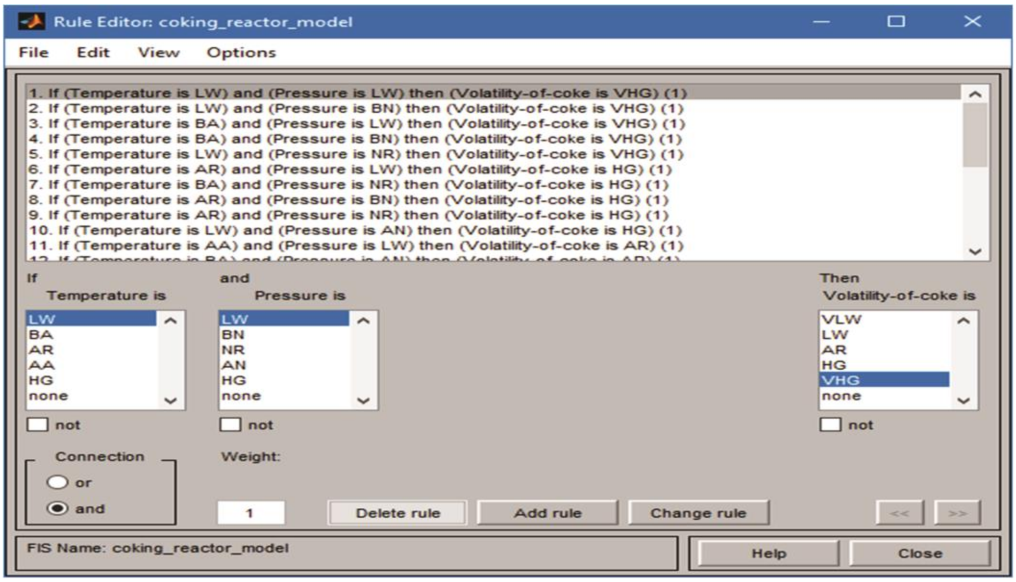

Figure 5. Fuzzy knowledge base for input and output parameters.

The results of fuzzy inference visualization in the RuleViewer are shown in Figure 6. The ***Input*** field contains the values of the input variables for which the inference is performed.

The input–output surface, which corresponds to the obtained fuzzy system, which allows to visually view the results of fuzzy modeling, is shown in Figure 7.

4.2. Development of Mathematical Models of DCU Coking Reactors

As a result of system analysis and expert evaluation of coking reactor operating modes, the following input, operating parameters were determined that affect the volume and quality of coke produced: x_1—loading (volume) of raw materials; x_2 and x_3—temperature and pressure of coking reactors; x_4—indicator of coking capacity of raw materials; x_5—recirculation coefficient.

The structures of fuzzy models of coking reactors are identified based on the modified method of sequential inclusion of regressors [27] and the method of synthesizing CTS mathematical models based on information of a different nature [30] in the following form:

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{5} \tilde{a}_{ij} x_{ij} + \sum_{i=1}^{5} \sum_{k=i}^{5} \tilde{a}_{ikj} x_{ij} x_{kj}, \ j = \overline{1,3} \tag{3}$$

where ~—means the fuzziness of the corresponding parameters and coefficients; $\tilde{y}_j$, $j = \overline{1,3}$—fuzzy output parameters (volume of coke and its quality indicators: volatility and ash content of coke); x_{ij}, x_{kj}—input, mode parameters; $\tilde{a}_{0j}, \tilde{a}_{ij}, \tilde{a}_{ijk}$—identifiable fuzzy parameters (regression coefficients: free member, coefficients of the linear and non-linear parts of the model).

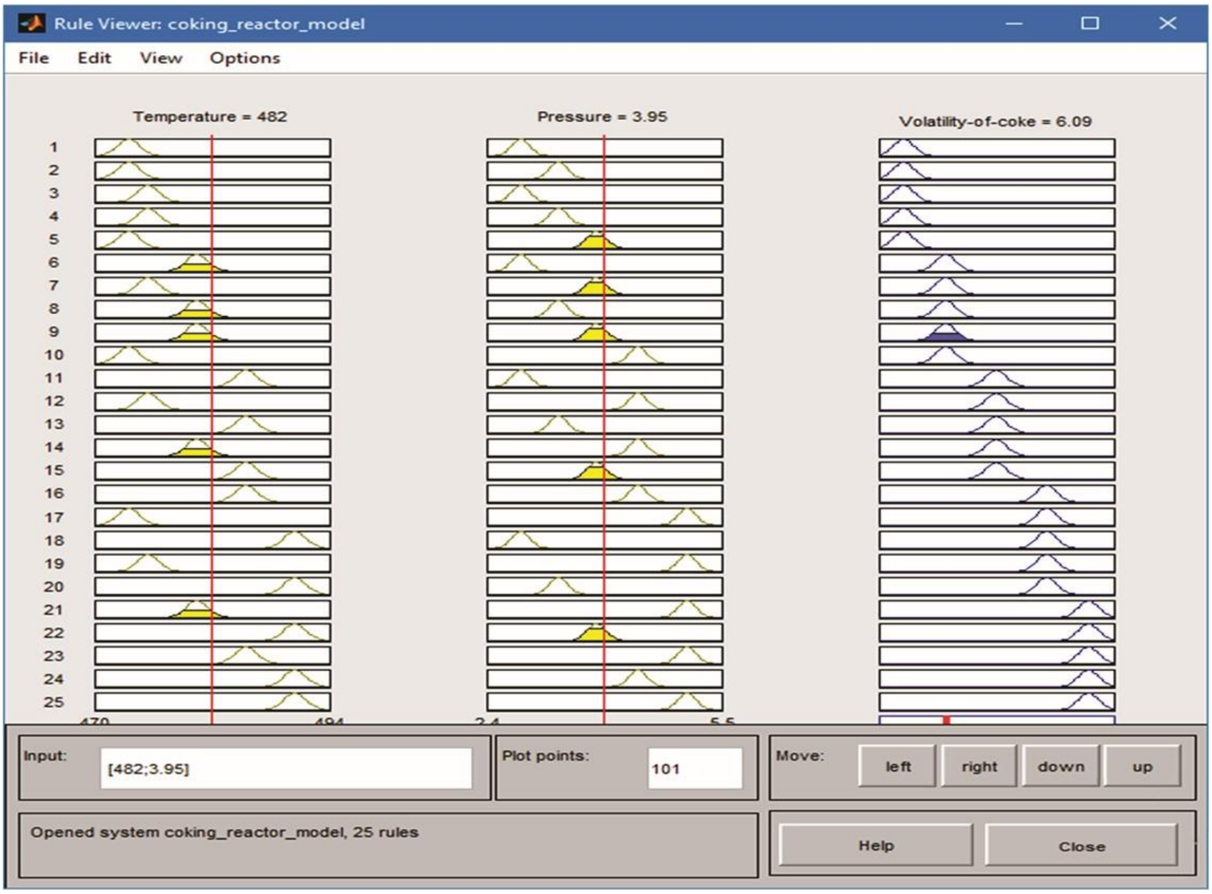

Figure 6. Visualization of fuzzy inference in RuleViewer.

To identify the fuzzy parameters of fuzzy models (3) based on the α-level set, it is necessary to convert fuzzy models to a system of crisp models. These models describe the influence of input, operating parameters on the volume and quality of coke with different accuracy (depending on the α value):

$$y_j^{a_l} = a_{0j}^{a_l} + \sum_{i=1}^{5} a_{ij}^{a_l} x_{ij} + \sum_{i=1}^{5} \sum_{k=i}^{5} a_{ikj}^{a_l} x_{ij} x_{kj},\ j = \overline{1,3} \tag{4}$$

In the system of Equation (4) $L_\alpha = \{\alpha_l, l = \overline{1,5},\ \alpha = (0.5; 0.85; 1.0; 0.85; 0.5)\}$—is the set of α-level, which determines the accuracy levels of crisp models. Then, to identify the fuzzy coefficients $\widetilde{\alpha}_{0j}, \widetilde{\alpha}_{ij},\ \widetilde{\alpha}_{ikj}$ of models (3), it is sufficient to determine the coefficients $\alpha_{0j}^{\alpha_l},\ \alpha_{ij}^{\alpha_l},\ \alpha_{ikj}^{\alpha_l}$ of crisp models (4), that satisfy the following condition (6) at each α-level:

$$J_j = \sum_{i=1}^{5} \left(y_j^{\alpha_l} - \hat{y}_j^{\alpha_l} \right)^2 \to \min, \quad l = \overline{1,5}, \tag{5}$$

where $\hat{y}_j^{\alpha_l}$—the value $y_j^{\alpha_l}$, obtained on the basis of expert information processing.

Then, the problem of identifying fuzzy coefficients of fuzzy models (3) is reduced to the problem of identifying crisp coefficients of the resulting crisp models (4) on α-level sets using well-known parametric identification methods, for example, the least squares method.

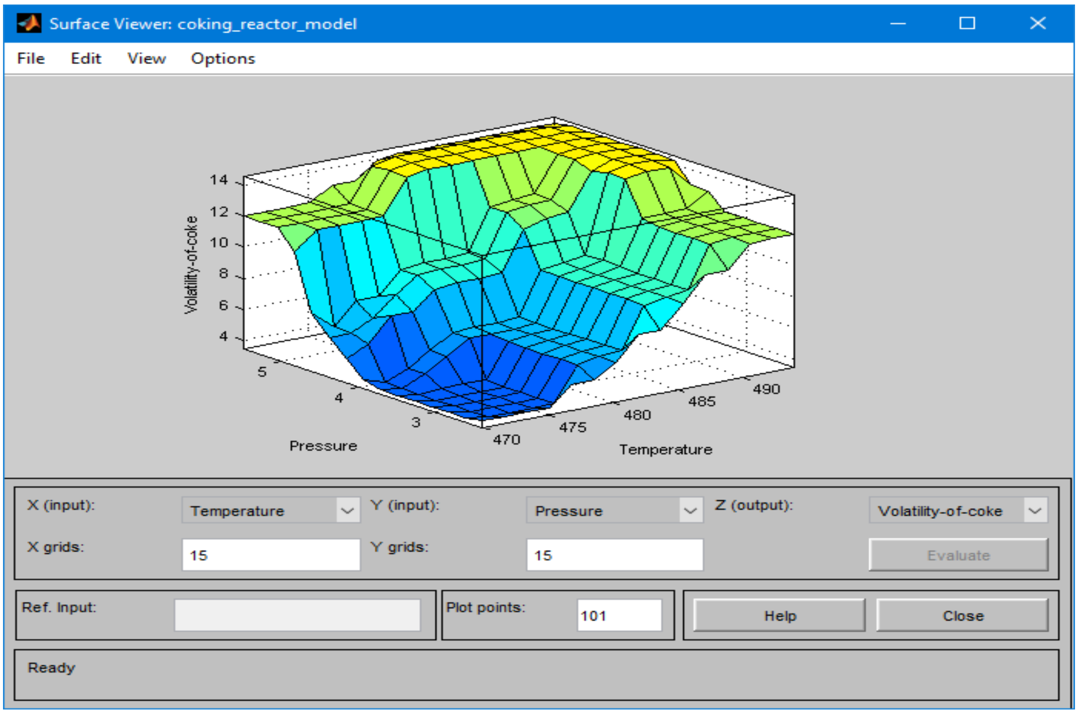

Figure 7. The input–output surface in SurfaceViwer.

On the selected level sets: $\alpha = (0.5; 0.85; 1.0; 0.85; 0.5)$ the values of the output parameters of coking reactors $\widetilde{y}_1$, $\widetilde{y}_2, \widetilde{y}_3$ are determined. Thus, for each $\alpha = (0.5; 0.85; 1.0; 0.85; 0.5)$ a set of crisp models has been obtained that allows estimating the volume of coke at the outlet of the coking reactors and the quality indicators of the produced coke.

To identify the parameters of the models in this work, we used the REGRESS software package, which implements the least squares method [26]. As a result, the models describing the dependence of the coke volume and its quality on the input, operating parameters of the coking reactors, after parametric identification on the level set $\alpha = (0.5; 0.85; 1.0; 0.85; 0.5)$ have the form of ordinary regression equations at the selected α levels.

The model estimating the volume of coke $\widetilde{y}_1$ ding on the input, operating parameters x_1, x_2, x_3, x_4, x_5n the selected α-level sets after parametric identification by the least squares method is given in Appendix A. Models estimating the volatility $\widetilde{y}_2$ and ash content $\widetilde{y}_3$ of coke depending on the input, operating parameters, after parametric identification in a similar way on the selected α-level sets, are given in Appendices B and C, respectively.

The obtained regression coefficients at different levels $\alpha_{ij}^{\alpha_l}$, $i = \overline{0,5}$, $j = \overline{1,3}$, $q = \overline{1,3}$ then for modeling on a computer will be combined according to the well-known formula of the theory of fuzzy sets (6):

$$\widetilde{a}_{ij} = \bigcup_{\alpha \in [0.5 \div 1]} a_{ij}^{\alpha_l} \text{ or } \mu_{\widetilde{a}_{ij}}(a_{ij}) = \sup_{\alpha \in [0,5 \div 1]} \min\left\{\alpha_l, \mu_{a_{ij}}^{\alpha_l}(a_{ij})\right\}, \tag{6}$$

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

The volume of oil product vapors from the output of coking reactors y_4 is determined using a regression-type model developed on the basis of experimental and statistical data [4]. Results of parametric identification of regression coefficients using the REGRESS program:

$$\begin{aligned} y_4 = {} & 157.165x_1 + 3.445x_2 - 28.085x_3 - 12.07x_5 + 0.988x_1^2 + 0.557x_2^2 - 0.156x_3^2 + \\ & + 0.334x_1x_2 + 0.015x_1x_2 + 0.185x_1x_5 - 0.05x_2x_3 + 0.045x_2x_5 + 0.004x_3x_5. \end{aligned} \tag{7}$$

4.3. Statement of Problems of Multicriteria Optimization of the Delayed Coking Process in a Fuzzy Environment and Development of a Heuristic Method for Its Solution

Let $\mu_0(\mathbf{x}) = \left(\mu_0^1(\mathbf{x}), \mu_0^2(\mathbf{x})\right)$ be the volumes of coke and vapors of oil products from coking reactors, which are normalized criteria, where $\mathbf{x} = (x_1, x_2, x_3, x_4, x_5)$—e vector of input, operating parameters of the reactors described above. Assume for fuzzy constraints on the quality indicators of coke $\varphi(\mathbf{x})\tilde{\geq} b_q,\ q = 1,2$: "coke volatility no more than $\tilde{\geq}$14%» and "coke ash content no more than $\tilde{\geq}$0.8%» the functions of their implementation $\mu_q(\mathbf{x}),\ q = 1,2$ are constructed. Suppose that the priorities of criteria $I_C = \{1,2\}$ and constraints $I_R = \{1,2\}$, the vector of weight coefficients for criteria $\boldsymbol{\gamma} = (\gamma_1,\ \gamma_2)$ and fuzzy constraints $\boldsymbol{\beta} = (\beta_1,\ \beta_2)$ are known or determined by DM, experts.

Then, the mathematical formulation of the problem of multicriteria optimization of the coking process based on the modification of the principles of the main criterion (MC) [31] and Pareto optimality (PO) [32] in general form can be written as:

$$\max_{\mathbf{x}\in X} \mu_0^1(\mathbf{x}), \tag{8}$$

$$X = \left\{\mathbf{x} : \mathbf{x} \in \Omega \wedge \arg\left(\mu_0^2(\mathbf{x}) \geq \mu_R^2\right) \wedge\ \underset{\mathbf{x}\in\Omega}{\operatorname{argmax}} \sum_{q=1}^{2} \boldsymbol{\beta}_q \mu_q(\mathbf{x}) \wedge \sum_{q=1}^{2} \boldsymbol{\beta}_q = 1 \wedge \boldsymbol{\beta}_q \geq 0,\ q = \overline{1,2}\right\}, \tag{9}$$

where $\mu_0^1(\mathbf{x})$ и $\mu_0^2(\mathbf{x})$—normalized main criterion estimating the volume of coke and the volume of vapors of oil products from coking reactors; $\mathbf{x} = (x_1, x_2, x_3, x_4, x_5)$—vector of input, operating parameters of coking reactors; $\wedge$—logical «and»; β_q *and* $\mu_q(\mathbf{x})$, $q = 1,2$—weight coefficients of fuzzy constraints and their membership functions.

To solve the resulting problem (8)–(9), the heuristic method MC + PO developed in Section 2 is used. Let us describe the results of the application.

1. Defined for each q-th coordinate $p_q, q = 1,2$, the number of steps: $p_1 = 5,\ p_2 = 2$ for constraints and a number of priority criteria $I_C = \{1,2\}$, where 1 is the priority of the volume of coke, 2 is the priority of the volume of vapors of petroleum products.
2. The values of weight coefficients of fuzzy constraints $\boldsymbol{\beta} = (\beta_1, \beta_2) = (0.6,\ 04)$, are defined and introduced, reflecting the mutual of these constraints.
3. Boundary values for local criteria are determined, which are taken into account as part of the constraints $\mu_R^2 = 6\ \text{m}^3$.
4. Step lengths are calculated using the formula $h_q = 1/p_q\ :\ \ h_1 = 1/5 = 0.2$; $h_2 = 1/5 = 0.2$, to change the coordinates of the vector $\boldsymbol{\beta} = (0.6,\ 04)$.
5. Changing the coordinates in the intervals [0, 1] with a step $h_1 = 0.2$ *and* $h_2 = 0.2$, the weight coefficients are determined $\beta_1, \beta_2, \ldots, \beta_N$, where $N = (5+1)\cdot(2+1) = 18$.
6. Term-sets are defined that describe fuzzy constraints and membership functions are constructed that estimate the degree of their fulfillment $\mu_q(\mathbf{x}),\ q = 1,2$.

The task has two fuzzy restrictions on the quality indicators of coke: "coke volatility must be less than $\tilde{\leq}$14%»; "the ash content of the coke must be less than $\tilde{\leq}$7%». For a fuzzy description of these qualitative indicators of coke, the term set $T(Y)$ = {low, medium, high} is defined. For each term, membership functions are constructed that estimate the degree of fulfillment of fuzzy constraints according to the Gaussian-type formula: $\mu_1^t(x) = e^{(Q_t|y_i - y_i^m|^{N_t})}$, where t—the term number; Q_t *and* N_t—coarse and fine tuning coefficients identified when approximating the function graph; y_i *and* y_i^m —a fuzzy parameter and the maximum corresponding numerical value (where the membership function takes the maximum value). Thus, the membership functions for volatility $\mu_1^k(x),\ k = \overline{1,3}$ and ash content of coke $\mu_2^k(x),\ k = \overline{1,3}$ are constructed in the following form:

$$\mu_1^1(x) = e^{(0.5|y_2 - 6|^{0.60})};\ \ \mu_2^1(x) = e^{(0.3|y_3 - 0.4|^{0.15})};$$

$$\mu_1^2(x) = e^{(0.5|y_2 - 10|^{0.55})};\ \ \mu_2^2(x) = e^{(0.3|y_3 - 0.6|^{0.12})};$$

$$\mu_1^3(x) = e^{(0.5|y_2-15|^{0.50})};\ \mu_2^3(x) = e^{(0.3|y_3-0.9|^{0.10})}.$$

7. Using the mathematical models of coking reactors developed in Section 2, the problem of maximizing the main criterion $\mu_0^1(\mathbf{x})$ (coke volume) on an admissible set X (9) is solved. Current solutions defined: $\mathbf{x}(\mu_R^2, \boldsymbol{\beta})$; $\mu_0^1(\mathbf{x}(\mu_R^2, \boldsymbol{\beta})), \ldots, \mu_0^m(\mathbf{x}(\mu_R^2, \boldsymbol{\beta}))$; $\mu_1(\mathbf{x}(\mu_R^2, \boldsymbol{\beta})), \ldots, \mu_L(\mathbf{x}(\mu_R^2, \boldsymbol{\beta}))$.
8. DM analyzed the obtained current solutions. Since in the first four solutions the DM is not satisfied with the current solutions, in order to iteratively improve the solution, he corrected μ_R^2 and $\boldsymbol{\beta}$ and the transition was carried out back to point 3. On the 5th cycle, the best results were obtained that satisfied DM, and the transition was made to the next point 9.
9. The best solutions chosen by DM are derived: $\mathbf{x}^*(\mu_R^2,\ \boldsymbol{\beta})$, which provide the maximum value of the main criterion $\mu_0^1(\mathbf{x}^*(\mu_R^2,\ \boldsymbol{\beta}))$, not worse than the boundary value of the criterion $\mu_0^2(x^*(\mu_R^2,\ \boldsymbol{\beta}))$ and maximum degrees of fulfillment of fuzzy constraints $\mu_1(x^*(\mu_R^2,\ \boldsymbol{\beta}))$, $\mu_2(x^*(\mu_R^2,\ \boldsymbol{\beta}))$. These results are listed in Table 3.

Table 3. Results of optimization of the coking process by the known deterministic method [33], the proposed heuristic method and experimental results of optimization at the Atyrau Refinery.

Criterion and Fuzzy Constraints	Deterministic Method	Heuristic Method *MC* + *PO*	Experimental Method
Coke volume, t/h—criterion y_1;	22.5	23.7	23.0
The volume of vapors of petroleum products, t/h—criterion y_2;	8.0	8.5	8.4
Membership functions of fuzzy constraints: Coke volatility $\tilde{\geq}$ 12%»—$\mu_1(x^*(\mu_R^2,\ \boldsymbol{\beta}))$	–	1.0	$(\cdot)^L$
Ash content $\tilde{\leq}$0.8 % vol.»: –$\mu_2(x^*(\mu_R^2,\ \boldsymbol{\beta}))$;	–	1.0	$(\cdot)^L$
Optimal parameters of DCU coking reactors: x_1^*—volume of raw material (tar); t;	105	105	105
x_2^*—coking reactor temperature, °C;	489	487	488
x_3^*—coking reactor pressure, kg/cm^2;	5.0	5.0	5.0
x_4^*—coking capacity of raw materials, %;	7	7	7
x_5^*—recirculation ratio.	11	11	11

Note:—means that these parameters are not determined by this method; $(\cdot)^L$—these parameters are not directly measured, are evaluated in the laboratory with the participation of a person; final values $\mu_R^2 = 8$; and $\boldsymbol{\beta} = (0.75,\ 0.25)$.

5. Discussion of Results

The constructed linguistic models of the DCU coking reactors using the proposed method of synthesizing linguistic models make it possible to fuzzily model the coking process in the Fuzzy Logic Toolbox and select the optimal mode of operation of the reactors. As can be seen from the results of fuzzy modeling, from the "input-output" surface in the SurfaceViwer (Figure 7), the lower the temperature and pressure of the reactors, the lower the coke volatility, i.e., the coke quality improves, and vice versa. This corresponds to the developed base of rules. Hence the conclusion is that it is necessary to choose a compromise solution when choosing the values of the input parameters of the reactors, since on the one hand, they allow increasing the volume of coke while, on the other hand, worsening its quality. To do this, it will be necessary to solve the decision-making problem of choosing the best compromise solution.

The results of fuzzy inference visualization in the Rule Viewer (Figure 6) allow to review the rules for the fuzzy inference of each rule, the resulting fuzzy set, and the implementation of the defuzzification procedure. Figure 6 shows the simulation results in the case when the input parameters are entered: the values of the reactor temperature are 482 °C and the pressure is 3.95 kg/cm^2. Then, as a result of fuzzy modeling, the volatility, i.e., the quality of the coke, is equal to 6.09. This means that the quality of the coke is quite high, since for high-quality coke, the volatility should not be higher than 12. Thus, by changing the values of the input parameters of the reactors, i.e., simulating their operating modes, it is possible to evaluate and select the best values for the coke quality.

In the developed models of coke reactors in 4.2, the input, operating parameters, and volume of produced steam of oil products are crisp, and the volume of coke and its coke quality indicators are fuzzy. To identify the structure and parameters of fuzzy models, modified methods of successive inclusion of regressors (for structural identification) and the least squares method (for parametric identification) were used. The essence of the modification of these methods is to represent the fuzzy regression equation as a set of clear regression equations at each set of α-level. To identify the parameters of the regression coefficients at α levels, the REGRESS software package was used. Then the obtained values of the coefficients at α levels are combined into one value using Formula (6) of the fuzzy set theory.

As a result of the analysis and discussion of the optimization results obtained by the proposed heuristic method and the deterministic method given in Table 3, the following advantages of the proposed MC + PO heuristic method can be distinguished:

1. The proposed MC + PO heuristic method allows solving the optimization problem in a fuzzy environment without converting the original fuzzy problem to deterministic ones. Since when converting a fuzzy problem to a set of deterministic problems, a part of the original, collected fuzzy information is lost, the adequacy of the solutions obtained decreases. The proposed heuristic method, due to the maximum use of the initial fuzzy information, makes it possible to obtain highly adequate solutions to the problem of decision making in a fuzzy environment. In addition, as can be seen from Table 3, the proposed heuristic method more accurately matches real, experimental data compared to the deterministic method.
2. The proposed heuristic method for solving the decision-making problem using fuzzy information, which is the experience, knowledge, and intuition of the DM, takes into account its preferences and non-formalizable links between criteria and alternatives. This allows the DM to make more efficient decisions about production problems in a fuzzy environment.
3. In contrast to deterministic methods, the developed heuristic method based on the principles of optimality (MC and PO) makes it possible to determine the values of the membership function of fuzzy constraints, i.e., the degrees of their fulfillment. This makes it possible to solve the problem of making decisions with fuzzy constraints, which does not allow solving other methods.
4. The proposed principle of developing a heuristic approach to solving decision-making problems in a fuzzy environment allows developing other heuristic methods based on the modification and combination of other optimality principles, such as maximin, ideal point, etc. This allows the DM, when solving decision-making problems, depending on the current production situation and the availability of initial information, to choose and use a more efficient method.

The optimization results presented in Table 3 show that the proposed heuristic method for solving a multicriteria optimization problem with fuzzy constraints provides better results compared to known deterministic methods. This is justified by the fact that the heuristic method makes it possible to improve the values of the criteria (the volume of coke by 5.33%, the volume of vapors of petroleum products by 6.25%) compared to the deterministic method with full fulfillment of the requirements of fuzzy constraints ($\mu_1\left(x^*\left(\mu_R^2,\ \boldsymbol{\beta}\right)\right) = 1$, and $\mu_2\left(x^*\left(\mu_R^2,\ \boldsymbol{\beta}\right)\right) = 1$).

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

6. Conclusions

The problems of modeling and optimization of the delayed coking process in a fuzzy environment are investigated, and approaches to their solution are proposed. Details of the main findings of the study and conclusions include:

(1) A method for synthesizing linguistic models has been developed, which allows synthesizing linguistic models based on fuzzy information from DMs, experts, representing their experience, knowledge, and intuition in natural language. Unlike other well-known methods for developing models with crisp input and fuzzy output parameters, the proposed method allows synthesizing CTS linguistic models with fuzzy both input and output parameters of the system. The proposed method of linguistic synthesis is systemic and comprehensively uses the logical rules of conditional inference, methods of expert assessments, and fuzzy set theories. Such a systematic application of the listed methods is required due to the effect of synergy and the property of emergence in order to obtain an effective solution to the problems under study, which cannot be obtained using separate methods.

(2) Based on the modification and combination of the principles of optimality of the main criterion and Pareto optimality, the proposed heuristic method allows to effectively solve problems of multicriteria optimization in a fuzzy environment. The proposed heuristic method differs from the known methods for solving fuzzy optimization problems in the fact that the problem is posed and solved in a fuzzy environment without preliminary transformation of the original fuzzy problem into a set of crisp problems. This allows to save and maximize the use of the collected fuzzy information, i.e., knowledge and experience of DM, experts to get more efficient and adequate solutions to a production problem in a fuzzy environment.

In the above analysis and comparisons of the results of solving the problem of optimization of the delayed coking process by the proposed heuristic method and deterministic method (Table 3), the advantages and effectiveness of the proposed approach are substantiated. In the proposed heuristic method for solving problems of two-criteria optimization with fuzzy constraints, the degree of fulfillment of fuzzy constraints is estimated by the values of the membership function of these constraints $\mu_1\left(x^*\left(\mu_R^2,\ \boldsymbol{\beta}\right)\right)$ и $\mu_2\left(x^*\left(\mu_R^2,\ \boldsymbol{\beta}\right)\right)$. As can be seen from Table 1, the values of these functions are equal to 1, which means complete (100%) fulfillment of the requirements of fuzzy constraints.

(3) On the basis of the proposed methods, linguistic models of coking reactors are synthesized, which make it possible to evaluate the quality of coke depending on the temperature and pressure of the reactors, and the problem of two-criteria optimization with fuzzy constraints is effectively solved.

The novelty of the proposed methods and results lies in the effective use of the knowledge, experience, and intuition of DM, experts in the development of models and solving problems of multicriteria optimization.

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Conflicts of Interest: The authors declare no conflict of interest.

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
$\widetilde{A}_i,\ i=\overline{1,n},\ \widetilde{B}_j,\ j=\overline{1,m}$	fuzzy subsets, input, output parameters of CTS
$\mathbf{x}=(x_1,\ldots,x_n)$	vector of input, mode parameters of the object
$\mathbf{y}=(y_1,\ldots,y_m)$	vector of output parameters of the object
$x_i,\ i=\overline{1,n}$	input, mode parameters of the object
$y_j,\ j=\overline{1,m}$	output parameters of the object
$\widetilde{x}_i,\ i=\overline{1,n}$	fuzzy input, mode parameters of the object
$\widetilde{y}_j,\ j=\overline{1,m}$	fuzzy output parameters of the object
$\widetilde{R}_{ij}$	fuzzy mappings between input, output linguistic variables of CTS
$\mu_{\widetilde{R}_{ij}}\left(\widetilde{x}_i,\widetilde{y}_j\right)$	fuzzy relationship matrices describing fuzzy relationships
$\boldsymbol{\beta}=(\beta_1,\ldots,\beta_L)$	weight vector of fuzzy constraints
$\mu_0(\mathbf{x})=\left(\mu_0^1(\mathbf{x}),\ldots,\mu_0^m(\mathbf{x})\right)$	normalized vector of criteria
$\mu_R^i,\ i=\overline{2,m}$	boundary values of local criteria specified by DM (except for the main ones)
$\mu_q(\mathbf{x}),\ q=\overline{1,m}$	membership functions that evaluate the degree of fulfillment of fuzzy constraints

Appendix A. Model Estimating the Volume of Coke Depending on the Input, Operating Parameters

$$
\begin{aligned}
\widetilde{y}_1 = &-\left(\tfrac{0.5}{287.1710}+\tfrac{0.85}{288.1720}+\tfrac{1}{289.1725}+\tfrac{0.85}{290.1727}+\tfrac{0.5}{291.1731}\right)+\left(\tfrac{0.5}{11.581900}+\tfrac{0.85}{11.583900}+\tfrac{1}{11.585940}+\tfrac{0.85}{11.587950}+\tfrac{0.5}{11.589537}\right)x_1+\\
&+\left(\tfrac{0.5}{8.711019}+\tfrac{0.85}{8.711024}+\tfrac{1}{8.711029}+\tfrac{0.85}{8.711034}+\tfrac{0.5}{8.711039}\right)x_2+\left(\tfrac{0.5}{71.08033}+\tfrac{0.85}{71.08323}+\tfrac{1}{71.08333}+\tfrac{0.85}{71.08353}+\tfrac{0.5}{71.08373}\right)x_3-\\
&-\left(\tfrac{0.5}{0.77850}+\tfrac{0.85}{0.87850}+\tfrac{1}{0.97890}+\tfrac{0.85}{0.99000}+\tfrac{0.5}{0.00550}\right)x_4-\left(\tfrac{0.5}{0.010301}+\tfrac{0.85}{0.011201}+\tfrac{1}{0.011701}+\tfrac{0.85}{0.012054}+\tfrac{0.5}{0.013515}\right)x_5+\\
&+\left(\tfrac{0.5}{0.00150}+\tfrac{0.85}{0.00250}+\tfrac{1}{0.01250}+\tfrac{0.85}{0.02250}+\tfrac{0.5}{0.03070}\right)x_1^2+\left(\tfrac{0.5}{0.16525}+\tfrac{0.85}{0.17700}+\tfrac{1}{0.18758}+\tfrac{0.85}{0.19750}+\tfrac{0.5}{0.28354}\right)x_2^2+\\
&+\left(\tfrac{0.5}{0.002739}+\tfrac{0.85}{0.005539}+\tfrac{1}{0.005739}+\tfrac{0.85}{0.005939}+\tfrac{0.5}{0.006857}\right)x_3^2+\left(\tfrac{0.5}{0.16028}+\tfrac{0.85}{0.160685}+\tfrac{1}{0.160988}+\tfrac{0.85}{0.161010}+\tfrac{0.5}{0.16358}\right)x_1x_2-\\
&-\left(\tfrac{0.5}{1.00000}+\tfrac{0.85}{1.30000}+\tfrac{1}{1.50000}+\tfrac{0.85}{1.70000}+\tfrac{0.5}{1.90000}\right)x_1x_3+\left(\tfrac{0.5}{0.044307}+\tfrac{0.85}{0.045117}+\tfrac{1}{0.04537}+\tfrac{0.85}{0.04567}+\tfrac{0.5}{0.045970}\right)x_1x_5+\\
&+\left(\tfrac{0.5}{1.122220}+\tfrac{0.85}{1.21220}+\tfrac{1}{1.22222}+\tfrac{0.85}{1.23225}+\tfrac{0.5}{1.32220}\right)x_2x_3-\left(\tfrac{0.5}{0.1000850}+\tfrac{0.85}{0.121940}+\tfrac{1}{0.131944}+\tfrac{0.85}{0.141937}+\tfrac{0.5}{0.151970}\right)x_3x_4-\\
&-\left(\tfrac{0.5}{0.018710}+\tfrac{0.85}{0.021720}+\tfrac{1}{0.029722}+\tfrac{0.85}{0.035720}+\tfrac{0.5}{0.04850}\right)x_3x_5.
\end{aligned}
$$

Appendix B. Model Estimating the Volatility of Coke Depending on the Input, Operating Parameters

$$
\begin{aligned}
\widetilde{y}_2 = {} & \left(\tfrac{0.5}{592600}+\tfrac{0.85}{593300}+\tfrac{1}{593800}+\tfrac{0.85}{594300}+\tfrac{0.5}{595000}\right)-\left(\tfrac{0.5}{23.7045}+\tfrac{0.85}{23.9450}+\tfrac{1}{24.1345}+\tfrac{0.85}{24.3350}+\tfrac{0.5}{24.5455}\right)x_1- \\
& -\left(\tfrac{0.5}{20.0170}+\tfrac{0.85}{20.3265}+\tfrac{1}{20.5278}+\tfrac{0.85}{20.7580}+\tfrac{0.5}{21.0590}\right)x_2+\left(\tfrac{0.5}{1.00850}+\tfrac{0.85}{1.11900}+\tfrac{1}{1.23950}+\tfrac{0.85}{1.3490}+\tfrac{0.5}{1.45950}\right)x_3+ \\
& +\left(\tfrac{0.5}{3.26100}+\tfrac{0.85}{3.47200}+\tfrac{1}{3.68330}+\tfrac{0.85}{3.89500}+\tfrac{0.5}{3.10650}\right)x_4+\left(\tfrac{0.5}{0.00350}+\tfrac{0.85}{0.0140}+\tfrac{1}{0.02450}+\tfrac{0.85}{0.03500}+\tfrac{0.5}{0.04550}\right)x_5+ \\
& +\left(\tfrac{0.5}{0.00070}+\tfrac{0.85}{0.00150}+\tfrac{1}{0.03330}+\tfrac{0.85}{0.06330}+\tfrac{0.5}{0.0943}\right)x_1^2+\left(\tfrac{0.5}{0.01350}+\tfrac{0.85}{0.01900}+\tfrac{1}{0.02430}+\tfrac{0.85}{0.02930}+\tfrac{0.5}{0.03850}\right)x_2^2- \\
& +\left(\tfrac{0.5}{0.01500}+\tfrac{0.85}{0.01100}+\tfrac{1}{0.01010}+\tfrac{0.85}{0.01350}+\tfrac{0.5}{0.01550}\right)x_3^2+\left(\tfrac{0.5}{0.32050}+\tfrac{0.85}{0.421500}+\tfrac{1}{0.52180}+\tfrac{0.85}{0.62250}+\tfrac{0.5}{0.7230}\right)x_4^2+ \\
& +\left(\tfrac{0.5}{0.28050}+\tfrac{0.85}{0.3810}+\tfrac{1}{0.48150}+\tfrac{0.85}{0.58200}+\tfrac{0.5}{0.68250}\right)x_1x_2+\left(\tfrac{0.5}{0.02050}+\tfrac{0.85}{0.03100}+\tfrac{1}{0.04150}+\tfrac{0.85}{0.05200}+\tfrac{0.5}{0.06250}\right)x_1x_3- \\
& -\left(\tfrac{0.5}{5.06400}+\tfrac{0.85}{5.08100}+\tfrac{1}{5.09260}+\tfrac{0.85}{5.10350}+\tfrac{0.5}{5.10850}\right)x_1x_4-\left(\tfrac{0.5}{0.17300}+\tfrac{0.85}{0.18030}+\tfrac{1}{0.19440}+\tfrac{0.85}{0.19950}+\tfrac{0.5}{0.20700}\right)x_2x_3+ \\
& +\left(\tfrac{0.5}{0.0635}+\tfrac{0.85}{0.0715}+\tfrac{1}{0.0755}+\tfrac{0.85}{0.0800}+\tfrac{0.5}{0.08850}\right)x_2x_4
\end{aligned}
$$

Appendix C. Model Estimating the Ash Content of Coke Depending on the Input, Operating Parameters

$$
\begin{aligned}
\widetilde{y}_3 = {} & \left(\tfrac{0.5}{269.54137}+\tfrac{0.85}{270.86715}+\tfrac{1}{271.94169}+\tfrac{0.85}{272.9427}+\tfrac{0.5}{273.94567}\right)-\left(\tfrac{0.5}{1.099005}+\tfrac{0.85}{1.09933}+\tfrac{1}{1.099537}+\tfrac{0.85}{1.09973}+\tfrac{0.5}{1.099985}\right)x_1- \\
& -\left(\tfrac{0.5}{0.64015}+\tfrac{0.85}{0.64032}+\tfrac{1}{0.640525}+\tfrac{0.85}{0.64072}+\tfrac{0.5}{0.64052}\right)x_2-\left(\tfrac{0.5}{2.662925}+\tfrac{0.85}{2.67300}+\tfrac{1}{2.683102}+\tfrac{0.85}{2.693225}+\tfrac{0.5}{2.703330}\right)x_3- \\
& -\left(\tfrac{0.5}{0.044750}+\tfrac{0.85}{0.054700}+\tfrac{1}{0.06478}+\tfrac{0.85}{0.0746}+\tfrac{0.5}{0.0847}\right)x_4+\left(\tfrac{0.5}{0.001090}+\tfrac{0.85}{0.001100}+\tfrac{1}{0.001111}+\tfrac{0.85}{0.00130}+\tfrac{0.5}{0.001150}\right)x_5+ \\
& +\left(\tfrac{0.5}{0.009500}+\tfrac{0.85}{0.001000}+\tfrac{1}{0.001019}+\tfrac{0.85}{0.001035}+\tfrac{0.5}{0.001058}\right)x_1^2+\left(\tfrac{0.5}{0.007325}+\tfrac{0.85}{0.007530}+\tfrac{1}{0.007639}+\tfrac{0.85}{0.007750}+\tfrac{0.5}{0.007967}\right)x_2^2+ \\
& +\left(\tfrac{0.5}{0.000125}+\tfrac{0.85}{0.00150}+\tfrac{1}{0.000174}+\tfrac{0.85}{0.000195}+\tfrac{0.5}{0.000230}\right)x_3^2+\left(\tfrac{0.5}{0.025250}+\tfrac{0.85}{0.025420}+\tfrac{1}{0.025679}+\tfrac{0.85}{0.025860}+\tfrac{0.5}{0.026075}\right)x_4^2- \\
& +\left(\tfrac{0.5}{0.062435}+\tfrac{0.85}{0.06275}+\tfrac{1}{0.062963}+\tfrac{0.85}{0.063005}+\tfrac{0.5}{0.063201}\right)x_1x_2-\left(\tfrac{0.5}{0.00043}+\tfrac{0.85}{0.00050}+\tfrac{1}{0.000556}+\tfrac{0.85}{0.000610}+\tfrac{0.5}{0.000685}\right)x_2x_3+ \\
& +\left(\tfrac{0.5}{0.277620}+\tfrac{0.85}{0.27770}+\tfrac{1}{0.277778}+\tfrac{0.85}{0.277805}+\tfrac{0.5}{0.277895}\right)x_2x_4+\left(\tfrac{0.5}{0.029015}+\tfrac{0.85}{0.02910}+\tfrac{1}{0.029167}+\tfrac{0.85}{0.02924}+\tfrac{0.5}{0.029310}\right)x_3x_4- \\
& -\left(\tfrac{0.5}{0.0010980}+\tfrac{0.85}{0.001010}+\tfrac{1}{0.001111}+\tfrac{0.85}{0.001215}+\tfrac{0.5}{0.001320}\right)x_3x_5.
\end{aligned}
$$

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