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# FORECASTING AND OPTIMIZATION OF CATALYTIC CRACKING UNIT OPERATION UNDER CONDITIONS OF FUZZY INFORMATION

**Abstract:** This paper discusses the application of nonlinear regression to forecast and optimize the operation of catalytic cracking units under conditions of fuzzy information. Catalytic cracking is a crucial process in oil refining that produces high-quality gasoline and other light hydrocarbon products. However, the complexity of the process and the uncertainty of initial data complicate the modeling and optimization of plant operations. To address this issue, a nonlinear regression method is proposed that accommodates the fuzziness of input and output parameters described by linguistic variables. The methodology includes the collection and formalization of expert knowledge, the construction of fuzzy models, and their integration into the process control system. Forecasting is performed by creating regression models that describe the relationships between operational parameters and product quality characteristics. The paper presents a procedure for developing and applying nonlinear regression models, describes algorithms for synthesizing linguistic models, and provides examples of their use


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to optimize the operation of catalytic cracking units. The modeling results demonstrate the high adequacy and accuracy of the proposed method, as well as its advantages over traditional approaches in conditions of uncertainty and data scarcity. The scientific novelty of the research lies in the development and testing of advanced nonlinear regression models adapted for analyzing and optimizing catalytic cracking processes based on fuzzy data. These methods take into account the specificity and uncertainty of process data, improving the accuracy and reliability of forecasts, which facilitates more effective management of production processes in the petrochemical industry. The main reason for conducting this study is the need to improve the control of oil refining processes, particularly catalytic cracking, which plays an important role in producing high-quality gasoline. The complexity of this process and the presence of fuzzy information caused by fuzzy initial data require the development of new modeling and optimization methods.

Existing traditional models based on deterministic methods are often insufficient under uncertainty. This leads to a decrease in the accuracy of process control, which can negatively affect the quality of the final product and production efficiency. The use of nonlinear regression in combination with fuzzy logic is a more flexible and adaptive approach that allows you to take into account the fuzziness and uncertainty of data and use expert knowledge to build models that match the actual operating conditions of the units. Thus, this study aims to solve the key problems associated with data uncertainty and the complexity of the catalytic cracking process, which will improve the accuracy of forecasting and optimization of the units. The main contribution is creating a model that uses nonlinear regression methods in combination with fuzzy logic. This allows uncertainty in input data (such as reactor temperature or pressure) to be effectively considered and processed to improve gasoline and other product yield forecasts. It is shown that using nonlinear regression combined with fuzzy logic significantly improves the management of technological processes, increases the output and quality of products, and reduces production costs. The conclusion of the paper discusses the prospects for further development of the methodology and its application to solve similar tasks in other areas of chemical technology.

**Keywords:** catalytic cracking; nonlinear regression; fuzzy logic; optimization; forecasting; technological processes; oil refining.

## Introduction

Catalytic cracking is one of the most important processes in the oil refining industry, transforming heavy oil fractions into light hydrocarbon products such as high-octane gasoline. The efficiency and stability of catalytic cracking units directly affect the quality and volume of products produced, making the task of optimizing and managing these units critically important. However, the complexity of the technological process and the uncertainty associated with the quality characteristics of the raw materials and changing operating conditions present significant challenges for traditional modeling and management methods.

These factors include variability of feedstock quality, process parameters such as temperature, pressure, catalyst consumption, and data uncertainty that arises during unit operation. The main problem is that traditional deterministic models used to predict and optimize catalytic cracking units are not effective enough in the presence of incomplete or fuzzy data. These models require accurate process and input information, which is often not available in real conditions. This leads to reduced forecast accuracy, and instability of production processes, which in turn reduces gasoline yield and quality.

Fuzzy information present in the data about the technological process complicates the application of classical deterministic models and requires the use of more flexible and adaptive approaches. One such approach is the method of nonlinear regression, which allows the

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VOLUME 19, SEPTEMBER 2024

consideration and processing of fuzzy information, as well as the use of expert knowledge to build adequate process models.

Thus, the research problem is to develop and implement methods that can operate effectively under uncertainty, allowing for accurate modeling and optimization of catalytic cracking unit performance despite fuzzy data and changing operating conditions.

The goal of this work is to explore the possibilities of applying nonlinear regression to forecast and optimize the operation of catalytic cracking units under conditions of fuzzy information. The research will develop nonlinear regression models that describe the relationships between input operational parameters and output process characteristics. These models will be integrated into the process control system for automatic parameter adjustment and improved efficiency indicators.

The research methodology includes: collecting and analyzing data on the operation of catalytic cracking units, including fuzzy information and expert assessments; building and validating nonlinear regression models using fuzzy logic methods; developing algorithms to optimize the operation of units based on the models obtained; and evaluating the effectiveness of the proposed models and algorithms through modeling and experimental studies.

Optimization and management of the catalytic cracking process have always been the focus of researchers, as the efficiency of this process affects production indicators and the economic profitability of refineries [1]. Historically, various methods have been used to model catalytic cracking processes, including kinetic modeling, deterministic models, and finite element methods. Research [2] discusses approaches to dynamic modeling of catalytic cracking, which include models based on kinetic equations and chemical thermodynamics. These methods provide high accuracy when complete and accurate data are available, but they become less effective under conditions of uncertainty and data scarcity [3].

In recent decades, there has been growing interest in using fuzzy logic and expert systems to model and manage complex technological processes, including catalytic cracking. Fuzzy logic allows for the consideration of uncertainty and variability in input data, as well as the use of expert knowledge to create adequate models. Research [4] explores various aspects of using fuzzy logic for managing catalytic cracking processes, including the development of fuzzy controllers [5] and decision support systems [6].

In addition to fuzzy logic, machine learning methods and neural networks are actively researched for forecasting and optimizing technological processes. These methods allow models to be trained on large data sets and to adapt to changing operating conditions. Research [7] discusses successful examples of using neural networks to model catalytic cracking processes, significantly improving the accuracy of forecasts and enhancing efficiency indicators.

The work [8] is devoted to the study of deep learning methods for modeling and predicting product yield in catalytic cracking units, which improves the accuracy of process control.

However, in these and other analyzed works addressed 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].

Nonlinear regression methods provide powerful tools for modeling complex dependencies between process variables [10]. Combined with fuzzy logic and machine learning methods, nonlinear regression allows for the creation of hybrid models that take into account both quantitative and qualitative aspects of the process [11]. Research [12] explores approaches to using nonlinear regression to model and optimize the operation of catalytic cracking units under conditions of fuzzy information.

Despite significant progress in the modeling and optimization of catalytic cracking processes, unresolved problems and challenges remain. One of the main limitations is the need for a large volume of high-quality data for training models and validating them. There is also a need to develop methods that can more effectively integrate expert knowledge into the modeling process [13].

The literature review shows that using nonlinear regression methods combined with fuzzy logic and machine learning provides promising opportunities for improving the management of catalytic cracking processes under conditions of uncertainty [14]. Further research in this area can contribute to the development of more accurate and adaptive models, leading to increased efficiency and profitability of production.

It is expected that the use of nonlinear regression in combination with fuzzy logic will allow for more accurate and effective forecasting of the behavior of catalytic cracking units, optimize their operation, and improve the quality of the products produced. The results of this research may be useful for further development of methods for managing complex technological processes under conditions of uncertainty and limited data.

**Methods and Materials**

The subject of this study is the reactor-regenerator section of the heavy residue catalytic cracking unit Title 1000 at the Shymkent Oil Refinery. The catalytic cracking unit for heavy residues, titled 1000, is designed to produce a high-octane component for automotive gasoline and liquefied hydrocarbon gases through the 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 pseudo-fluidized circulating high-dispersion aluminosilicate-based catalyst.

The main technological process takes place in the reactor-regenerator section of the unit. The sections of this block—the reactor and the regenerator—are closely interconnected. The primary cracking process occurs in the reactor by adding the catalyst to the feedstock of the unit. As a result of cracking, coke is formed, which reduces the activity of the process. The coke formed on the catalyst is burned off during regeneration. Figure 1 shows the technological scheme of the reactor-regenerator section of the catalytic cracking unit at the Shymkent Oil Refinery.

The technological scheme, Figure 1 represents a complex system of catalytic cracking that includes a reactor, regenerator, heat exchangers, and control systems for the effective conversion of raw materials into gasoline. Main attention is paid to maintaining temperature and pressure, as well as regeneration and management of the catalyst to maintain the efficiency of the cracking process. Fuzzy logic is used to control process parameters such as reactor temperature, regenerator temperature, reactor pressure, feedstock and catalyst supply, and the regulation of other main system parameters. The goal of control is to optimize product output while also maintaining the necessary product quality.

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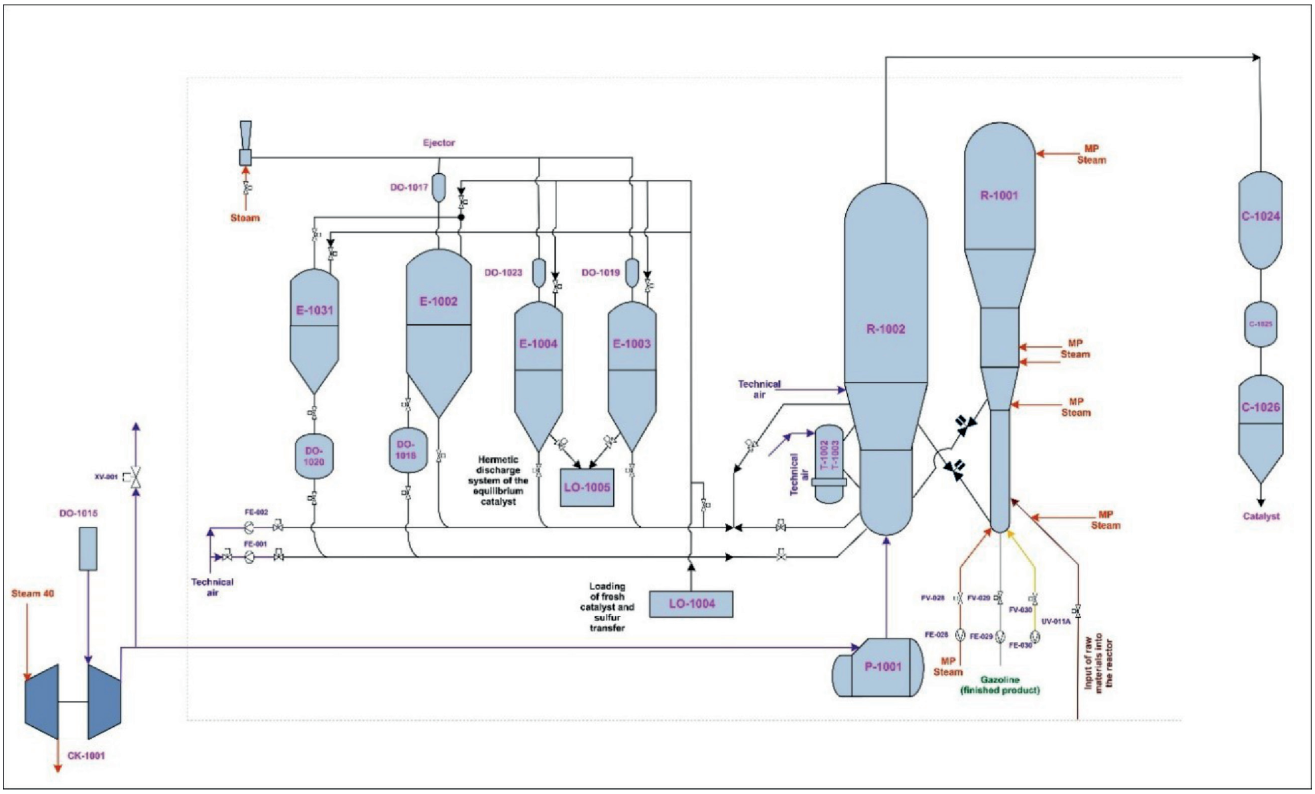

Figure 1. Flow chart of the reactor and regenerator unit of the catalytic cracking unit Title 1000

In the reactor, the primary process of catalytic cracking occurs, where heavy feedstock (e.g., fuel oil or vacuum gas oil) is subjected to high temperatures. A catalyst is added to the reactor to break down heavy hydrocarbon molecules into lighter fractions, such as gasoline and liquefied hydrocarbon gases. In the regenerator, the catalyst is regenerated after being coated with a layer of coke during the cracking process. Regeneration involves burning off the coke at high temperatures, which restores the catalyst's activity before its reuse. The feedstock delivery system involves the feedstock being transported to the reactor via pipelines, where it is preheated to the required temperature before contact with the catalyst. Heat exchangers are used to maintain the necessary temperature conditions for efficient cracking and to transfer heat between different streams in the system. The process parameter control system includes sensors and measuring instruments for monitoring and adjusting parameters such as temperature, pressure, and the flow of feedstock and catalyst. The catalyst circulates between the reactor and the regenerator, continually being regenerated and returned to the reactor for further use. The diagram demonstrates the interdependence of the reactor and regenerator, where maintaining optimal conditions for the catalytic process, such as temperature and pressure, as well as restoring the catalyst's activity, is crucial.

Figure 2 presents a flowchart of the nonlinear regression method. According to the method scheme, the process begins with the collection of initial data (independent and dependent variables). The data are pre-processed, which includes cleaning, missing value handling, scaling, and transformation. The next step involves selecting a model of nonlinear regression that describes the dependency, such as polynomial regression, logarithmic, exponential, etc. In model configuration, parameters like initial coefficients are defined. Optimization methods, such as the least squares method, are used to find the model coefficients. During the training stage, the model is trained using training data. Quality of the model is evaluated on validation data (error assessment, accuracy determination). Subsequently, the model is applied to forecast new data. Finally, the results are assessed, predicted values are analyzed, and if necessary, the process returns to the model tuning stage.

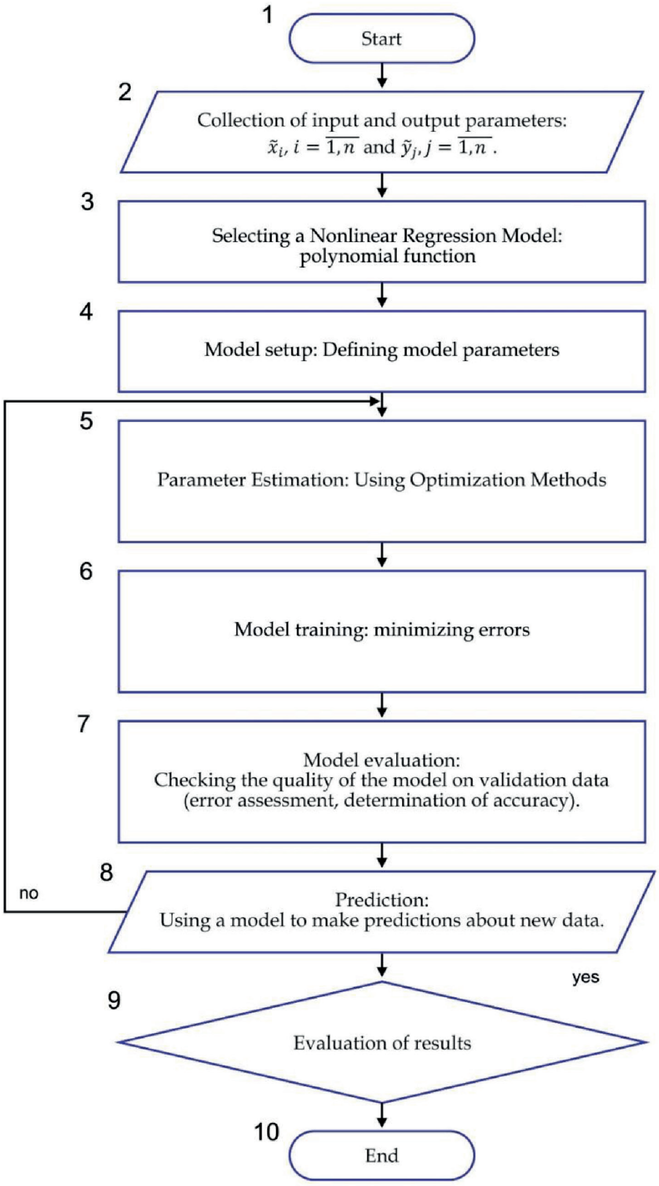


Figure 2. Flowchart of the nonlinear regression method.

For the development and validation of models, data were obtained from the technological regulations of the catalytic cracking unit at the Shymkent Oil Refinery, as well as data collected during the operation of the unit. Table 1 shows the main variables in the process of the unit, including controlled and measured variables.

Table 1. Main input, operating mode, and output parameters of the process

| 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$^3$ |

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VOLUME 19, SEPTEMBER 2024

Fuzzy logic methods were used to account for fuzzy information and uncertainty in data. The main stages in constructing fuzzy models include [15]:

1. Fuzzification:
   - Defining linguistic variables and their terms.
   - Creating membership functions for each linguistic variable.
2. Rule Base Construction:
   - Formalizing expert knowledge and creating a rule base in an “if-then” format.
3. Rule Aggregation:
   - Combining multiple rules to determine the final value of the output variable.
4. Defuzzification:
   - Transforming fuzzy output values into precise numerical values for result interpretation.

The rules constructed and the results from the application of fuzzy logic methods were discussed in the article [14].

For building regression models that describe relationships between input and output parameters, the method of nonlinear regression was utilized. The main steps include:

1. Model Selection:
   - Determining the type of nonlinear regression model (e.g., polynomial, exponential, logarithmic).
2. Model Parameter Estimation:
   - Using the method of least squares to estimate model parameters.
   - Applying optimization algorithms such as gradient descent to find optimal parameter values.
3. Model Validation:
   - Splitting data into training and test samples.
   - Evaluating model accuracy using metrics such as Mean Squared Error (MSE) and the coefficient of determination ($R^2$).

The model equation describes the dependency of process output parameters on input operational parameters. Consideration is given to the nonlinear regression model equation for two main output parameters: gasoline yield ($y_1$) and gasoline density ($y_2$).

The model equation for gasoline output $y_1$:

$$y_1 = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_5 x_5 + \alpha_6 x_6 + \alpha_7 x_1^2 + \alpha_8 x_2^2 + \alpha_9 x_3^2 + \alpha_{10} x_4^2 + \alpha_{11} x_5^2 + \alpha_{12} x_6^2 + \\ + \alpha_{13} x_1 x_2 + \alpha_{14} x_3 x_4 + \alpha_{15} x_5 x_6 + \varepsilon_1 \quad (1)$$

The model equation for the density of gasoline $y_2$:

$$y_2 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_1^2 + \beta_8 x_2^2 + \beta_9 x_3^2 + \beta_{10} x_4^2 + \beta_{11} x_5^2 + \\ + \beta_{12} x_6^2 + \beta_{13} x_1 x_2 + \beta_{14} x_3 x_4 + \beta_{15} x_5 x_6 + \varepsilon_2 \quad (2)$$

where: $y_1$ is the gasoline yield, $y_2$ is the gasoline density, $x_1$ is the raw material flow rate, $x_2$ is the raw material density, $x_3$ is the raw material temperature, $x_4$ is the reactor temperature, $x_5$ is the reactor pressure, $x_6$ is the catalyst flow rate, and $\alpha_0$, $\alpha_1$, … $\alpha_{15}$ the coefficients are for the regression model of gasoline yield and $\beta_0$, $\beta_1$, … $\beta_{15}$ gasoline density, and $\varepsilon_1$, $\varepsilon_2$ represent random errors.

These equations describe nonlinear relationships between the input operational parameters and the output characteristics of the catalytic cracking process. The regression model coefficients (for gasoline yield and gasoline density) are estimated using the method of least squares and optimization algorithms such as gradient descent.

To build and evaluate the regression models, data were used that were obtained from the technological regulations of the Shymkent Oil Refinery catalytic cracking unit. Below are the coefficient values for the nonlinear regression models describing gasoline yield ($y_1$) and gasoline density ($y_2$). The coefficients for the regression model of gasoline yield ($y_1$) and gasoline density ($y_2$) are provided in Table 2.

Table 2. Coefficients of the regression model for gasoline yield ($y_1$) and gasoline density ($y_2$)

| Coefficient for gasoline yield | Value | Coefficient for gasoline density | Value |
|---|---|---|---|
| $\alpha_0$ | 2.5 | $\beta_0$ | 0.6 |
| $\alpha_1$ | 0.12 | $\beta_1$ | 0.05 |
| $\alpha_2$ | -0.07 | $\beta_2$ | -0.02 |
| $\alpha_3$ | 0.15 | $\beta_3$ | 0.08 |
| $\alpha_4$ | 0.20 | $\beta_4$ | 0.12 |
| $\alpha_5$ | -0.10 | $\beta_5$ | -0.03 |
| $\alpha_6$ | 0.08 | $\beta_6$ | 0.04 |
| $\alpha_7$ | -0.01 | $\beta_7$ | -0.01 |
| $\alpha_8$ | 0.03 | $\beta_8$ | 0.02 |
| $\alpha_9$ | 0.02 | $\beta_9$ | 0.01 |
| $\alpha_{10}$ | -0.04 | $\beta_{10}$ | -0.02 |
| $\alpha_{11}$ | 0.05 | $\beta_{11}$ | 0.03 |
| $\alpha_{12}$ | 0.02 | $\beta_{12}$ | 0.01 |
| $\alpha_{13}$ | -0.03 | $\beta_{13}$ | -0.02 |
| $\alpha_{14}$ | 0.01 | $\beta_{14}$ | 0.01 |
| $\alpha_{15}$ | 0.04 | $\beta_{15}$ | 0.02 |

For estimating an output parameter, such as gasoline yield, it is necessary to substitute the values of the input parameters (raw material consumption, raw material density, etc.) into the corresponding equation and calculate the result. This allows you to predict the behavior of the process and optimize the parameters to achieve the best performance [16].

To calculate the gasoline yield (y1) with known values of the input parameters, for example, $x_1 = 150$, $x_2 = 0.8$, $x_3 = 200$, $x_4 = 500$, $x_5 = 2$, $x_6 = 1700$, it is necessary to substitute these values into the model equation and calculate $y_1$, $y_2$.

$$y_1 = 2.5 + 0.12x_1 + 0.07x_{2..} + 0.15x_3 + 0.20x_4 + 0.10x_5 + 0.08x_6 + 0.01x_1^2 + 0.03x_2^2 + 0.02x_3^2 + \\ + 0.04x_4^2 + 0.05x_5^2 + 0.02x_6^2 + 0.03x_1x_2 + 0.01x_3x_4 + 0.04x_5x_6 \quad (3)$$

Using this model equation, graphs were constructed depending on the output value from the input values (Figures 3-5).

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VOLUME 19, SEPTEMBER 2024

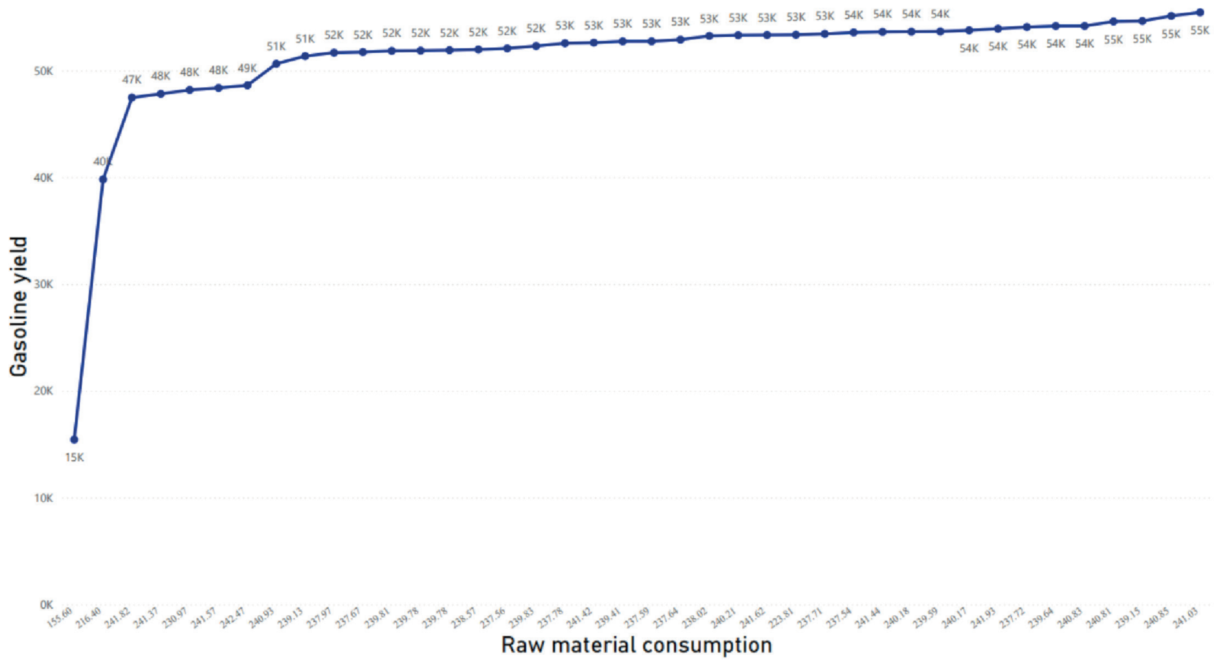


Figure 3. Dependence of gasoline yield on raw material consumption

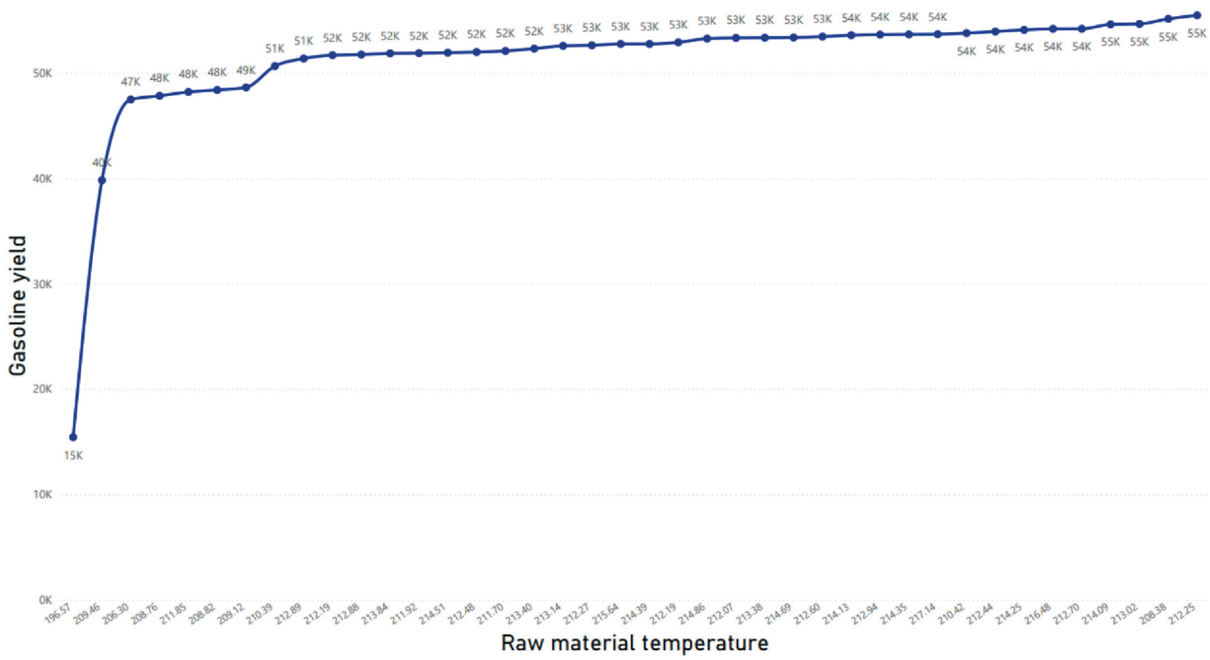


Figure 4. Dependence of gasoline yield on raw material temperature

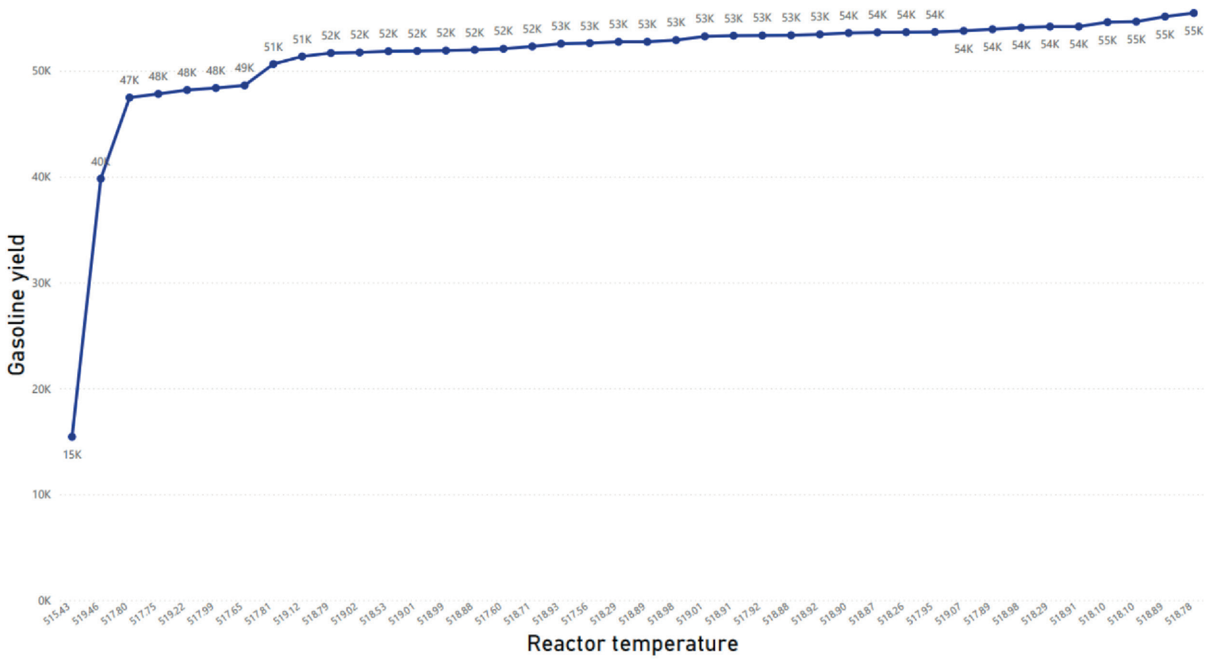


Figure 5. Dependence of gasoline yield on reactor temperature

Such calculations allow predicting the output parameters of the process, optimizing the operation of the plant, and making informed decisions to improve production efficiency.

Using these equations in the control system allows automatic adjustment of the catalytic cracking process parameters, ensuring increased production efficiency and improved product quality.

To assess the effectiveness of the developed methods and models, a series of experiments and simulations were conducted, the results of which were compared with actual data and plant performance indicators. The main evaluation criteria include [17]:

- Accuracy of forecasting output parameters.
- Improvement of process efficiency indicators (product yield, product quality).
- Reduction of production costs and increase in the stability of the plant operation.

The results of the study demonstrate the high efficiency of using the nonlinear regression and fuzzy logic methods for modeling and optimizing the operation of catalytic cracking units. In the future, it is planned to expand the study to include a wider range of parameters and operating conditions, as well as to develop more complex hybrid models to improve the accuracy and adaptability of control systems.

**Results and Discussion**

Within the scope of this study, nonlinear regression models were developed that describe the relationships between input operational parameters and output characteristics of the catalytic cracking process. The main results include:

- Regression Models: Models were constructed that account for the fuzziness of data and describe complex nonlinear dependencies between parameters. The models include input parameters such as raw material flow rate, raw material density, reactor temperature, reactor pressure, and catalyst flow rate.
- Accuracy Indicators: The accuracy of the models was evaluated using the metrics MSE (Mean Squared Error) and $R^2$ (Coefficient of Determination). The obtained MSE and $R^2$ values indicate the high adequacy of the models and their ability to accurately predict the output parameters of the process.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 19, SEPTEMBER 2024

Table 4. Accuracy of nonlinear regression models

| Parameter | MSE | $R^2$ |
|---|---|---|
| Gasoline output (%) | 0.015 | 0.95 |
| Density of gasoline | 0.010 | 0.92 |

The developed fuzzy models were integrated into the control system of the catalytic cracking process. The main results of the integration include:

- Rule Base Creation: A rule base was established based on expert knowledge, describing the dependencies between input and output parameters. An example of a rule is: «If reactor temperature is high and raw material flow rate is low, then gasoline yield is medium.»
- Aggregation and Defuzzification: The developed aggregation and defuzzification algorithms enabled the transformation of fuzzy inputs into precise control actions. This facilitated the possibility of automatically adjusting process parameters in real-time.

As a result of applying the developed models and algorithms, significant improvements were achieved in the operation of the catalytic cracking unit. The main results include:

- Increased Product Yield: The application of fuzzy logic and nonlinear regression allowed for an increase in gasoline yield by 5-7% compared to traditional control methods.
- Improved Product Quality: The density of gasoline became more stable and in line with specified standards, indicating an improvement in product quality [18].
- Cost Reduction: Optimizing process parameters led to reduced costs for raw materials and energy resources, enhancing the economic efficiency of the plant operation. Table 5 presents the results of the optimization of the plant.

Table 5. Optimization Results of the Plant Operation

| Indicator | Before optimization | After optimization | Change (%) |
|---|---|---|---|
| Gasoline yield (%) | 50 000 | 55 000 | +10 |
| Gasoline density | 0.740 | 0.735 | -0.68 |
| Raw material costs | 1000 | 950 | -5 |
| Energy costs | 500 | 475 | -5 |

The analysis of the simulation results demonstrated the high adequacy and accuracy of the developed models. The main conclusions include:

- Conformity to Real Data: The models exhibited a high degree of correspondence with actual data obtained during experiments at the catalytic cracking facility.
- Flexibility and Adaptability of Models: Fuzzy models and nonlinear regression methods proved effective under conditions of uncertainty and changing process parameters.

The study results demonstrate the potential of applying nonlinear regression and fuzzy logic methods for modeling and optimizing complex technological processes.

Plans include:

- Database Expansion: Collection and analysis of additional data to improve the accuracy and reliability of the models.
- Development of Hybrid Models: Integration of machine learning methods and neural networks to create more complex and accurate models.
- Testing and Implementation: Conducting additional experiments and pilot implementations at other facilities to confirm the effectiveness of the developed methods.

Thus, the application of nonlinear regression and fuzzy logic significantly enhances the management of the catalytic cracking process, increases product yield and quality, and reduces production costs.

The analysis of modeling results demonstrates the high accuracy and adequacy of the developed nonlinear regression models. The Mean Squared Error (MSE) values and Coefficient of Determination ($R^2$) indicate that the models are successful in predicting the output parameters of the catalytic cracking process. High $R^2$ values (0.95 for gasoline yield and 0.92 for gasoline density) confirm that a significant portion of the variability in output parameters is explained by the input variables included in the models.

Integration of fuzzy models into the control system has shown significant improvement in the operation of the catalytic cracking unit. A rule base developed based on expert knowledge has enabled the creation of an adaptive system that effectively responds to changes in process parameters. The application of aggregation and defuzzification methods has provided smooth and precise adjustment of parameters, leading to improved production indicators [19].

One of the key outcomes of applying the developed methods is an increase in gasoline yield by 5-7% and an improvement in its quality (reduced density). This demonstrates that the models can not only accurately predict output parameters but also optimize the process to achieve better results. Cost reductions in raw materials and energy resources also confirm the economic efficiency of the proposed approach.

Compared to traditional catalytic cracking process control methods, the application of fuzzy logic and nonlinear regression shows advantages. Unlike deterministic models, which require precise and complete data, fuzzy models can operate effectively under conditions of uncertainty and data scarcity. This makes them more flexible and adaptable, which is particularly important in real production environments.

The use of fuzzy logic has allowed for the incorporation of expert knowledge and intuition of operators, significantly enhancing the accuracy and reliability of the models. The use of linguistic variables and fuzzy rules has provided the ability to describe complex dependencies between process parameters that are difficult to formalize using traditional methods. This is especially important for managing processes where there are significant uncertainties and variability in input data [20].

Despite the achieved results, the study has some limitations. Firstly, the quality of the models heavily depends on the volume and quality of the initial data [21]. Secondly, the effectiveness of fuzzy models and nonlinear regression methods may decrease under changing operational conditions that were not accounted for during model development. Plans include expanding the database, incorporating new parameters and operating conditions, and developing hybrid models using machine learning methods and neural networks to increase the accuracy and adaptability of control systems [22].

The research results confirm the high effectiveness of applying nonlinear regression and fuzzy logic methods for modeling and optimizing the operation of catalytic cracking units. The developed models and algorithms can be implemented in other oil refineries to improve production indicators and reduce costs. Further experiments and pilot implementations are planned, which will allow the validation and expansion of the obtained results.

Thus, the proposed approach represents a promising direction for the development of control methods for complex technological processes under conditions of uncertainty and data scarcity.

## Conclusion

In this study, the nonlinear regression method was explored for forecasting and optimizing the operation of catalytic cracking units under conditions of fuzzy information. The main results include the development and validation of nonlinear regression models, the integration of fuzzy models into the control system, and the optimization of process parameters to enhance production efficiency.

Key findings of this research:

1. Development of Adequate Models:
   - Nonlinear regression models demonstrated high accuracy in predicting the output parameters of the catalytic cracking process. The MSE and $R^2$ values confirmed the adequacy of the developed models.
2. Integration of Fuzzy Logic:
   - The integration of fuzzy models into the control system allowed for the consideration of data uncertainty and variability, as well as the use of expert knowledge to create a rule base. This provided more precise and adaptive process control.
3. Improvement of Production Indicators:
   - The application of the developed models and algorithms led to an increase in gasoline yield by 5-7%, improved its quality, and reduced costs for raw materials and energy resources. This confirms the economic efficiency of the proposed approach.
4. Flexibility and Adaptability:
   - Fuzzy models and nonlinear regression methods proved effective under conditions of uncertainty and changing process parameters, making them preferable over traditional deterministic methods.

Prospects for further research:

- Database expansion, i.e., incorporating a larger volume of data and additional parameters to improve the accuracy and reliability of the models.
- Development of hybrid models, integrating machine learning methods and neural networks to create more complex and accurate models.
- Testing and implementation, conducting additional experiments and pilot implementations at other facilities to validate and expand the obtained results.

The results of this study can be applied at other oil refining plants to improve the management of catalytic cracking processes. The application of nonlinear regression and fuzzy logic methods significantly enhances production indicators, reduces costs, and improves product quality.

In conclusion, the proposed approach represents a promising direction for the development of control methods for complex technological processes under conditions of uncertainty and data scarcity. Further development and implementation of these methods could lead to significant improvements in the oil refining industry and other sectors where managing complex processes is critically important.

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