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SYSTEM CONCEPT
FOR MODELLING OF TECHNOLOGICAL SYSTEMS AND DECISION MAKING IN THEIR MANAGEMENT

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The monograph is devoted to the system analysis of approaches to the building of models of chemical-technological systems, on the basis of which a systematic concept of building of models and the issues of solving decision-making problems for managing the operating modes of technological objects is proposed. The problems of the development of mathematical models and the optimization of complex chemical-technological systems are investigated, using the example of technological objects of oil refining, in conditions of uncertainty caused by the lack of reliable quantitative information and the fuzziness of available information.
The monograph is intended for students, undergraduates and doctoral students in the specialties of information technology, automation and control, researchers and specialists dealing with problems of modelling, optimization, decision-making in the management of technological systems of oil refineries.
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ABSTRACT

The monograph is devoted to the system analysis of approaches to the building of models of chemical-technological systems, on the basis of which a systematic concept of building of models and the issues of solving decision-making problems for managing the operating modes of technological objects is proposed. The problems of the development of mathematical models and the optimization of complex chemical-technological systems are investigated, using the example of technological objects of oil refining, in conditions of uncertainty caused by the lack of reliable quantitative information and the fuzziness of available information. The structure of the monograph consists of an introduction, the main part of four sections, a conclusion and a list of sources of information.

In the main part of the work, the current state of the problems of mathematical modelling of technological objects of oil refining production is analyzed. Methods of mathematical modelling and decision-making in the management of technological objects according to environmental and economic criteria are chosen as the direction of research. Methods of building mathematical models of chemical-technological systems of oil refining in a fuzzy environment have been investigated and proposed, and models of the technological complex of the catalytic reforming unit have been developed. An approach to the creation of a package of models for system modelling of the technological complex of the catalytic reforming unit is described. An algorithm for the synthesis of models of a technological complex of oil refining based on fuzzy information is proposed. Expert assessments have been carried out to develop a mathematical description of the technological complex of the reforming unit, a method has been developed for carrying out expert procedures in a fuzzy environment.

The formulations of decision-making problems for the control of the technological complex of the reforming unit are formulated and, based on the modification of various optimality principles, heuristic algorithms for their solution are developed. The properties of the developed algorithms for solving decision-making problems have been investigated and a method for their selection in solving specific production problems has been proposed. A mathematical formulation of the decision-making problem for optimizing the operating modes of the catalytic reforming unit in a fuzzy environment is obtained and the results of its solution based on the proposed fuzzy approach are presented. The structure is created and the main functional blocks of the computer decision support system based on the object models are described. The issues of software implementation of the developed models are considered and a description of the interface of the computer system for modelling the units of the reforming unit and decision support for optimizing their operation modes is given.

KEYWORDS

Mathematical model, multi-criteria optimization, decision making, fuzzy information, technological object of oil refining, catalytic reforming unit, system of modelling and decision-making support, decision maker.

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In this work, the following abbreviations and terms are used with the corresponding definitions:

A

A-14, A-15 – hydrogenate filters;

Absolute (relative) concession principle – principle according to which a multicriteria problem is reduced to a single-criterion one, by summing (product, summation of the logarithms of the criteria) taking into account their weight coefficients. The principle of absolute assignment can be formally expressed using the following notation:

$$F = \underset{F \in \Omega f}{\text{opt}}\, kF = \left\{ F \,/ \sum_{j \in J^+} \Delta f_j \geq \sum_{i \in I^-} \Delta f_j \right\},$$

where J^+ – subset of dominated criteria, that is, those for which $\Delta f_j > 0$; I^- – subset of minorized criteria, that is, those for which $\Delta f_j < 0$; Δf_j, Δf_j – the absolute value of the criteria increment; / – the symbol «such for which». The principle of relative concession can be written as:

$$F = \underset{F \in \Omega f}{\text{opt}}\, kF = \left\{ \sum_{j \in J^+} X_j \geq \sum_{i \in I^-} \Delta X_i \right\},$$

where $X_j = \Delta f_j / f_j^{max}$, $X_i = \Delta f_i / f_i^{max}$ – relative changes in criteria; f_j^{max}, f_i^{max} – maximum values of the criteria;

ACRC-106, 106a ACRC – air-cooled refrigerator-condenser;

ACS – automated control system – a man-machine system that ensures the effective functioning of the technological complex of the refinery, in which the collection and processing of information and the development of control actions is carried out on the basis of mathematical methods using computer technology;

ACS TP – automated control systems for technological processes, automated control systems for managing the technological part of the production complex;

Algorithm – sequence of actions that, by transforming the initial data, make it possible to obtain solutions to the problem;

Atyrau Refinery – Atyrau Oil Refinery.

B

Boolean Conditional Inference Rule – a rule used in the development of a linguistic model, which has the structure «If ____, then ____, or if ____, then _____, otherwise».

C

Catalizer	–	gasoline reforming product, characterized by a high octane number;
Catalyst	–	compounds to speed up the chemical process;
Catalytic reforming of gasoline	–	the most important process of modern oil refining and petrochemistry, serves for the simultaneous production of a high-octane base component of motor gasolines, aromatic hydrocarbons – feedstock for petrochemical synthesis – and hydrogen-containing gas (HSG) – technical hydrogen used in the hydrogenation processes of oil refining;
Combined models	–	models that are developed on the basis of information of a different nature, for example, statistical and fuzzy, etc;
Controlled factors	–	factors, the parameters of the choice of which are determined by decision-makers;
Criteria	–	indicators of the quantity and quality of products that need to be optimized;
CSM-DM	–	computer system that combines modeling methods, decision-making and the capabilities of modern computer technology, which can significantly improve and speed up the procedure for choosing the optimal solution. The CSM-DM includes the following main blocks: a set of algorithms for solving DM problems, a package of models, knowledge and data bases, model identifier and user interface;
CTS	–	chemical-technological system, which is a set of devices interconnected by flows and functioning as a whole in which various processes take place.

D

DEA	–	diethanolamine;
Decision maker	–	the decision-maker, in our cases – process operators, economists, ecologists, chooses the operation mode of the facility that provides the optimal values of local criteria, as a rule, economic, technological and environmental;
Delayed coking unit	–	designed to produce petroleum coke, which serves as a raw material for the electrode industry;
Deterministic models	–	developed on the basis of theoretical ideas about the structure of the described system and the regularities of the functioning of its individual subsystems, that is, these models are built on the basis of a theoretical approach;
Deterministic tasks	–	optimization problems in which the initial data are uniquely determined;
Dichloroethane	–	a reagent supplied to the reforming reactor to increase the activity of the catalyst;
DM	–	decision-making, a process that consists in evaluating possible solutions (alternatives) and choosing the best one according to specified criteria;

DM problems	–	<DM Problems>={given V, V_S, V_P, it is required to provide W}, where V – the given conditions; V_S – the set of possible states of the object; V_P – the set of possible operators that ensure the transition of an object from one state to another; W – the desired state of the object. In this case, the solution of the DM problem is to select a sequence of operators to transfer the object from the state at the current moment to the desired state;
DM problems at risk	–	(stochastic decision-making problems) arise in those cases when each decision $x_i \in \Omega$ is associated with a set of outcomes from m possible outcomes $S_1, \ldots, S_n$ with known probabilities $P(S_j \mid x_i)$, $j = \overline{1,n}$, $i = \overline{1,m}$, in these tasks there is no unambiguous connection between alternatives and outcome;
DM problems in a fuzzy environment.	–	decision-making situation when at least one of the elements of the problem (alternatives, criteria, preferences and restrictions) is not clearly described;
DM problems in conditions of certainty	–	(deterministic DM problems) are characterized by an unambiguous deterministic relationship between the alternatives X_i and the outcome S.
E		
EES	–	economic and ecological systems – production facilities in which various processes take place (determining the economic and ecological state of the facility) and a person is involved;
ELOU-AT-2 direct distillation unit	–	designed for the process of primary oil refining. Section ELOU (electrical desalting) is intended for oil preparation by electrical desalting and dehydration in an electric field, and the AT (atmospheric-tubular) section of the installation is intended for separating demineralized and dehydrated oil into separate fractions by heating it, evaporating, fractionating and condensing distillate vapors;
ELOU-AVT unit	–	(atmospheric-vacuum tubular) is designed for oil preparation at the electric desalting unit and processing at the atmospheric and vacuum units;
Equality principle	–	principle according to which the criterion or constraints by means of weighting factors are equal to each other;
Expert methods	–	methods that are organized and carried out in order to collect and process information from a person – a specialist-expert in conditions of deficit and lack of information (for the purpose of modeling and optimization).
F		
Fuzzy models	–	are built on the basis of methods of the theory of fuzzy sets and expert assessments with crisp input and fuzzy output parameters;
Fuzzy ratio R	–	on the set U is called a fuzzy subset of the Cartesian product UxU, which is characterized by the membership function μ_R: Ux$U \to [0,1]$ (μ_R: Ux$U \to L$).The value μ_R (U,U) of this function is understood as some subjective measure of the fulfillment of the relation URU (L – some arbitrary lattice);

Fuzzy set	– a fuzzy set $\tilde{A}$ on a universal set U is a collection of pairs $(\mu_A(U), U)$, where $\mu_A(U)$ – degree of membership of an element $U \in U$ in a fuzzy set $\tilde{A}$.
G	
Gasoline hydrotreating process	– a catalytic process that takes place in the HCG environment and ensures the decomposition and removal of organic compounds of sulfur, oxygen and nitrogen present in gasoline from raw materials.
H	
HC	– hydrocarbon;
HCG	– hydrogen-containing gas;
Hydrogenate	– product of the process of hydrotreating gasoline, feedstock for catalyzate;
Hydrotreating	– process of purification of raw materials from sulfur, nitrogen and oxygen-containing compounds using a catalyst.
I	
Ideal point method	– method that allows to find the optimal solution by minimizing the measure (distance) of the current solution from the ideal solution (point);
Identification	– determination of the structure of the mathematical model (structural identification) or unknown coefficients of the regression model (parametric identification);
Information model	– used as advisory systems to study the influence of factors on the output parameters for the development of recommendations for adjusting the mode of operation of the modeled object;
Intensification	– increasing the productivity of the facility – the quantity and quality of target products (using mathematical methods);
Interaction representation matrix	– method based on the matrix of representation of interactions, allows to identify the sources of danger in the technological process of oil refining, by presenting all theoretically possible binary interactions of substances found in this technological system;
Interface	– software product is designed to provide a convenient dialogue mode for the user with the system when managing an object, as well as when implementing a number of other CSMO functions;
Intersection of fuzzy sets	– intersection of fuzzy sets $\tilde{A}$ and $\tilde{B}$ given on U is a fuzzy set $\tilde{C} = \tilde{A} \cap \tilde{B}$ with a membership function $\mu_C(u) = \min(\mu_A(u), \mu_B(u))$ for all $u \in U$. The operation of finding the minimum is also denoted by a sign, i.e. $\mu_C(u) = \mu_A(u) \wedge \mu_B(u)$.
K	
Knowledge and data base	– intended for storing formalized knowledge of experts, researchers of the subject area and statistical data on production; it is one of the blocks of computer systems.

L

LG – Leningrad – Germany, a catalytic reforming unit manufactured in Leningrad using German technology;

Linguistic model – built on the basis of methods of the theory of fuzzy sets and logical rules of conditional inference with fuzzy input and output parameters;

Linguistic variables – variables whose values are words and sentences (fuzzy variables).

M

Main criterion method – method according to which the main (in importance) criterion is optimized, and the rest of the local criterion is included in the constraints;

Mathematical model – system of mathematical descriptions reflecting the features of the processes occurring in the object of modeling (technological unit), which, using a certain algorithm, makes it possible to predict the behavior of the object when the input and control parameters change;

Mathematical modeling – research of an object or process on the basis of a mathematical model in order to determine the optimal mode of operation;

Mathematical models package – combined in a single package mathematical models of interconnected technological units and for the purpose of system modeling;

Maximin principle – principle according to which the maximums are selected from the minimums, i.e. guaranteed result is provided, formally expressed as follows:

$$F = \operatorname{opt} k = \max \min f_q,\ F \in \Omega_f,\ F \in \Omega_f\ \ 1 \le q \le k.$$

If this principle is applied, an option with the minimum values of local criteria is selected from the area of compromises, and among them the option with the maximum value is sought;

Membership function $\mu_A(U)$ – called a function that allows to calculate the degree of membership of an arbitrary element of the universal set to a fuzzy set.

N

NMT problem – generalized class of problems of mathematical programming, which in special cases, the membership of fuzzy variables is transformed into ordinary problems of mathematical programming. Here, either objective functions, or restrictions, or all of them are characterized by fuzziness;

Normalization – reduction of parameters to the same units or dimensionless scale.

O

Oil – is a product of the synthesis of mainly two elements: carbon (79.5–87.5 %) and hydrogen (11.0–14.5 %);

Oil refining – is a set of physical and physical-chemical processes carried out at oil refineries (refineries), including the processes of preparing crude oil for processing, primary and deep processing of oil and oil products;

Optimal operating mode – operating mode of the object – values of operating and control parameters, providing an optimal solution;

Optimal solution	–	decision in which the selection criteria take extreme (best, maximum or minimum) values; The optimal solution X must satisfy the relation: $$F = F(X) = \text{opt}\left[F(X), \wedge\right], X \in \Omega_x,$$ where F – an optimal solution to the integral criterion; opt – an optimization operator, it determines the chosen optimization principle;
Optimization	–	search and finding the best parameter values (extreme maximum or minimum);
Optimization models	–	used to find the optimal conditions for the process in a complex of aggregates.

P

Parametric identification	–	identification of parameters (determination of coefficients) of mathematical models, which structures have already been identified;
Pareto principle of optimality	–	principle according to which the decision maker chooses the optimal solution from a set of no more than 5–7 criteria, which improvement of one of them leads to the deterioration of the other;
Petroleum coke calcination unit	–	designed to remove volatile components and moisture, and obtain calcined coke that meets the requirements;
Physicochemical processes	–	processes of oil and gas processing, oil fractions and processes of chemical and petrochemical synthesis; characterized by a change in the composition and structure of molecules with the formation of qualitatively new compounds;
Priority series	–	$\overline{R}$ is an ordered set of indices of local criteria $\overline{R} = \{1,2,\ldots,k\}$, the criteria, the indices of which are on the left, dominate over the criteria, the indices of which are on the right. In this case, dominance is qualitative: the f_1 criterion is always more important than f_2, etc.;
Process control models	–	are used to influence the system in real time in order to compensate for unwanted random disturbances and displacement of the system in the direction of the extreme value of the objective function.

Q

QEA	–	quality expert assessment – expert assessment, carried out in the fuzzy environment;
Qualitative information	–	information received from a person and representing its knowledge and experience, expressed in natural or professional language (meaningfully).

R

R-1	–	multi-chamber reforming furnace;
RC-6, 6a	–	refrigerators for reforming products;
Reactors R-2, R-3 and R-4, 4a	–	reforming reactors of a catalytic reforming unit, designed to carry out the reforming process;
Reforming	–	process of converting naphthenes and paraffins into aromatic hydrocarbons, i.e. increasing their octane number;

Regression analysis	–	method that allows the development of mathematical models based on the processing of statistical data;
Risk assessment	–	procedure for identifying sources of danger, assessing existing and potential hazards. Based on the results of the risk assessment, measures are developed to reduce the hazard level to an acceptable one.
S		
S-7	–	reforming high pressure separator;
S-8	–	reforming low pressure separator;
S-9	–	reforming circulating gas separator;
Set of the α-level of the fuzzy set $\tilde{A}$	–	a crisp subset of the universal set U, the elements of which have degrees of membership greater than or equal to a: $A_\alpha = \{u: \mu_A(u) \geq \alpha\},\ \alpha \in [0,1]$. A set α – level of a fuzzy set A is called an ordinary set A_α such that: $\mu_{A_\alpha}(x) = \begin{cases} 0 \text{ at } \mu_A(x) < \alpha, \\ 1 \text{ at } \mu_A(x) \geq \alpha; \end{cases}$
Statistical (stochastic) models	–	mathematical models that are based on the methods of probability theory and mathematical statistics;
Structural identification	–	determination of the structure of the mathematical model (for example, based on the method of sequential inclusion of regressors).
T		
T-6, 6a/1:4	–	product heat exchangers of the reforming unit;
Technical nitrogen	–	reagent used to flush the reforming system;
Technological installation	–	set of interconnected technological units designed to produce one or more products;
Term set	–	many possible meanings of linguistic variables (many terms, words);
TFS	–	theory of fuzzy sets – a mathematical apparatus that allows to formalize and use fuzzy information in the mathematical description of the process;
Thermocatalytic processes	–	it is widely used in oil refining and petrochemical production to improve the quality of feedstock and to obtain target products (for example, catalytic cracking, catalytic reforming, hydrotreating, hydrocracking).
U		
Uncontrollable factors	–	characterize the conditions in which the choice is made and which the decision maker cannot influence, for example, time;
Uniformity principle	–	proclaims the expediency of choosing a solution that would achieve a certain «uniformity» of indicators for all local criteria;
Union of fuzzy sets	–	union of fuzzy sets $\tilde{A}$ and $\tilde{B}$ given on U is a fuzzy set $D = \tilde{A} \cup \tilde{B}$ with a membership function $\mu_D(u) = \max(\mu_A(u), \mu_B(u))$ for all $u \in U$. The operation of finding the maximum is also denoted by a sign, i.e. $\mu_D(u) = \mu_A(u) \vee \mu_B(u)$.

READERSHIP

The monograph will be interesting and useful for senior students, undergraduates and doctoral students who study in the specialties of information technology, automation and control, and will also be useful for researchers and specialists dealing with problems of modelling, optimization, decision-making in the management of technological systems of oil refineries. In addition, the materials of the monograph can be used by teachers in the preparation and conduct of classes in the disciplines of mathematical modelling, optimization and decision-making.

The monograph is of interest for the field of systems analysis, theory and methods of mathematical modelling, multi-criteria optimization and decision-making, and will also be useful in solving problems of their application in practice. In addition, the monograph may be of interest in the field of sciences for the organization and conduct of expert assessments, formalization and use of the initial fuzzy information based on the theory of fuzzy sets for solving problems of modelling, optimization and management of complex chemical-technological systems of various industries, which are characterized by a deficit and fuzziness of the initial information.

Interest in the materials of the monograph is manifested in their structured presentation in theoretical and practical aspects, as well as the usefulness of the results in solving production problems for the optimization and control of operating modes of technological systems.

From a practical point of view, the monograph will be interesting for the oil regions of various countries, for example, for Western Kazakhstan and for other countries of the world where oil is extracted and processed. For the development of the economy in these regions, a higher priority is the effective management of oil refining processes based on mathematical models of technological objects and processes and making optimal decisions.

INTRODUCTION

The main problems of the development of production include the issues of its intensification, optimization of parameters, operating modes, ensuring an increase in the quality and efficiency of technological and production processes. One of the promising ways to address these issues is to increase the efficiency of management of production facilities through the use of scientifically based methods for developing and making decisions using the appropriate mathematical apparatus and computer technology. Such problems associated with improving the efficiency and quality of applied solutions are actively discussed in the scientific and technical literature. Currently, there is a series of works on the methods of modelling and optimization of complex industrial facilities, on the formalization and solution of DM problems in their management, many problems of an applied nature have been solved. However, there is a class of objects, various production situations and problems of their management, the formalization and solution of which cannot be obtained within the framework of traditional approaches or does not give significant results. These objects and problems include production systems operating under conditions of uncertainty associated with the indistinctness of initial information, and problems of formalizing and solving the problems of choosing rational modes of their operation in various production situations. In addition to the fuzziness of the initial information, the solution of these problems complicates the complexity and multicriteria of control objects.

Due to the complexity or impossibility of measuring a number of parameters and indicators, many production and technological processes are difficult to describe quantitatively, which makes it difficult to use the methods of deterministic mathematics for modelling and optimizing their operating modes. This led to the emergence of new methods of formalizing and solving the considered problems, which rely on fuzzy information received from experts, decision makers in the form of their judgments about the functioning of the object and taking into account their preferences in the process of choosing solutions.

Methods for formalizing and using such fuzzy information for the mathematical description of the functioning of a quantitatively difficult to describe object and for solving decision-making problems in the process of managing them are based on expert procedures and the methodology of the theory of fuzzy sets. Successful solution of the above problems of modelling and solving problems of multicriteria choice requires the development of a methodology for building fuzzy models of complex objects, such as production systems, further development of formalization methods and solving problems of managing them in a fuzzy environment, the development of algorithms and programs for the implementation of these methods using modern computers. These problems are the subject of research in this monograph.

Formulations of a family of multicriteria choice problems arising in the management of production facilities in a fuzzy environment formalized in this paper, methods for their solution, proposed approaches to building more efficient models of production facilities based on fuzzy information, the issues of creating intelligent systems to support decision-making in which the developed heuristic algorithms for solving DM problems are implemented in a dialogue with the decision maker; they are relevant in the problems of increasing production efficiency. The research results are promising for theory and expand the range of practical problems to be solved, make it possible to more accurately describe production situations and solve emerging problems.

For the efficient use of a large oil reserve in the country's economy, it is necessary to develop refining capacities to ensure a greater depth of processing of hydrocarbon raw materials and obtain high-quality oil products and petrochemical products. The main purpose of research work is related to these problems.

Despite the large oil potential, the regions of the Republic of Kazakhstan are in dire need of refined products, especially for the production of synthetic materials, plastics, motor fuels, lubricants, etc. To provide these products, production complexes for oil refining and petrochemistry are designed and implemented.

The average oil refining depth in the republic is 70 %. In this regard, first of all, it is necessary to develop a strategy for commissioning new capacities and optimal management of existing technology, taking into account the latest achievements of science and technology, incl. mathematical methods and computer technology that allow optimal control of technological objects and oil refining processes.

In the near future, it is necessary to do a lot of work on the introduction of new technologies at Kazakhstani oil refineries, which will help expand the range of products and improve their quality. These problems are dictated by market requirements, toughening environmental standards and the upcoming accession of Kazakhstan to the WTO.

Correct organization and effective implementation of the problems considered requires preliminary analysis and research work. The use of scientific forecasting and mathematical modelling methods ensures the effectiveness of the decision. Therefore, this monograph investigates and proposes effective methods for solving the problems of technological complexes based on new mathematical methods and the possibilities of modern computer technology.

The proposed modelling methods based on available information of various nature and decision-making methods in conditions of multicriteria and indistinctness of the initial information as applied to oil refining facilities will be implemented using the example of the process of obtaining high-octane gasoline at the catalytic reforming unit of the LG unit of the Atyrau refinery.

The relevance of the research topic. The intensive development of the oil refining industry in Kazakhstan requires scientifically grounded solutions to various production problems based on modern achievements of mathematical methods and computer technology.

The use of mathematical modelling methods in solving production problems, incl. a large number of studies have been devoted to the problems of the oil refining industry. However, the results of solving these problems under conditions of uncertainty, scarcity and indistinctness of the initial information are insufficient, there are relatively few works devoted to solving the considered problems under these conditions, there are many still unresolved issues. To effectively solve problems, an integrated method is needed that allows to develop a system of models of technological objects and make effective decisions on their management in real situations, characterized by uncertainty and fuzziness. These methods should take into account the active element of the production system – a person, its knowledge and experience, formalized in the form of fuzzy information and processed using the apparatus of the theory of possibilities (fuzzy mathematics).

For effective research and making optimal decisions when managing oil refining facilities, it is necessary to build their mathematical models that take into account the nature and state of the process, type, and other features of the facilities. Since technological objects of oil refining production are a complex complex of interconnected units, it is necessary to develop a package of models that allows the use of systemic modelling of the object. In addition, problems of multi-criteria and uncertainty of oil refining facilities often arise, which make it difficult to build the necessary mathematical models and optimization algorithms. As a result, the methods for synthesizing models under conditions of uncertainty and decision making (DM) developed in this monograph, taking into account the qualitative nature of the information collected and the multicriteria of the problem, are assumed to be extremely important and relevant.

The aim of research: conducting a systematic analysis of approaches to modelling and making decisions on the management of chemical-technological oil refining systems (using the example of a catalytic reforming unit) and creating a concept for building models of such systems based on complex information of a quantitative and qualitative nature.

Object and subject of research. The object of research in this work is the technological complexes of oil refining production on the example of the system of technological units of the catalytic reforming unit of the LG-35-11/300-95 unit of the Atyrau refinery. The subject of research is modern mathematical, incl. informal methods for solving production problems in conditions of a lack of initial information (expert assessments, modelling and decision-making) of research objects.

In accordance with the set aim, the following main objectives are being solved:

– study of the current state of the problems of mathematical modelling and decision-making on the choice of optimal operating modes of the technological complex of oil refining in the conditions;

– creation and implementation of a methodology for building a complex of models of interconnected technological units using the example of a reforming unit; development of an algorithm for the synthesis of linguistic models of technological objects of oil refining production in conditions of fuzzy input and output parameters; creation of a new method of expert assessment, which allows organizing and conducting an expert survey in a fuzzy environment based on high-quality information;

– development of a complex of combined models of the main units of the reforming unit (reactors R-2, R-3, R-4, 4a, furnace R-1) using known and proposed methods for building models;

– formalization and formulation of new multi-criteria DM problems for the selection of optimal operating modes of technological objects of oil refining on the example of a catalytic reforming unit and the development of a set of effective algorithms for their solution in a fuzzy environment;

– study of the proposed algorithms and solution of a specific DM problem for the selection of optimal operating modes of the reforming unit of the LG unit of the Atyrau refinery;

– research and creation of the structure and main blocks of a computer system for modelling and decision-making on the choice of optimal operating modes of technological objects of oil refining. Analysis of the prospects for the development of DM computer systems and the application of research results in science and industry.

Methods of research. The monograph uses a systematic approach and an integrated method, including: analysis and generalization of the achievements of mathematical methods in solving production problems of the oil refining industry; methods of mathematical modelling and decision making; methods of theories of possibilities and expert assessments; software systems and computer technology; industrial and experimental verification of research results and technical and economic analysis.

The scientific value of the work lies in the development of methodological foundations of mathematical modelling in conditions of uncertainty based on the development of a package of interrelated mathematical models of the aggregates of the complex with the use of available information of a different nature and the building of linguistic models, taking into account the internal connection between technological parameters and, due to the knowledge and experience of experts, providing the adequacy of models of hard-to-describe objects; in the formulation and solution of multi-criteria DM problems for the control of technological objects of oil refining, which, on the basis of modified compromise schemes and principles of optimality in the case of indistinctness of the initial information, allow finding effective solutions of production problems that satisfy the decision maker.

Practical value and implementation of work results. The proposed approach and the developed algorithm for the synthesis of mathematical and linguistic models of technological objects in conditions of uncertainty make it possible to build effective models and simulate technological complexes of oil refining, petrochemistry and other industries.

Formalized and posed multicriteria DM problems and developed algorithms for their solution, based on modified compromise schemes and optimality principles, and the proposed modelling methods allow to find the optimal modes of oil refining, petrochemical, mining, transport and other industries.

The developed methods of modelling and decision-making were used in the building of mathematical models of technological units of the catalytic reforming unit of the LG unit and in the selection of the optimal modes of their operation based on the obtained models.

1 CURRENT STATE OF PROBLEMS OF MATHEMATICAL MODELLING OF TECHNOLOGICAL FACILITIES OF OIL REFINING PRODUCTION

ABSTRACT

In this section, the analysis of the current state of the problems of mathematical modelling of complex technological systems on the example of interconnected units of technological units of oil refining production. The main characteristics of oil refining technological objects, consisting of interconnected technological units, are investigated and described, the issues of increasing the efficiency of their functioning according to economic and environmental criteria, as well as the issues of solving the problems of decision-making on the choice of optimal operating modes of the oil refining technological objects are considered.

As a result of the study of various approaches to the building of models of technological objects of oil refining and optimization of their operation, it has been established that the use of traditional methods of modelling and decision-making in industrial conditions is often ineffective due to the lack, inaccessibility or insufficiency of reliable quantitative information about the parameters and state variables of the objects. In these conditions, as a promising apparatus for formalizing, processing and using the initial fuzzy information, in the form of knowledge, experience and intuition of experts, in modelling and making decisions on the choice of optimal modes of technological objects, methods of expert assessments and the theory of fuzzy sets are recommended.

The developed mathematical models of objects are used to make decisions on the management of technological objects of oil refining according to environmental and economic criteria. The general formulation of the research problems is formulated, the problems arising in their solution and approaches to their solution are considered.

KEYWORDS

Mathematical modelling, technological object, modes of object operation, oil refining production, decision making problem.

1.1 APPROACHES TO THE MATHEMATICAL DESCRIPTION OF PRODUCTION SYSTEMS UNDER CONDITIONS OF UNCERTAINTY

Production systems include technical, technological and economic objects and their combinations, various industrial complexes designed for processing and creating material and other types of products, or providing certain services to society. It is these objects that form the basis of industrial production, consume most of the material energy, financial and human resources, represent the main object of application of the latest achievements of science and technology, determine the main directions of technical progress [1–3].

Modern production systems are a complex system consisting of a set of interconnected multi-mode subsystems, the functioning of which is aimed at achieving the overall goals of the system. The features of such a production system are: the presence of separated parts (subsystems, elements), for each of which the purpose of functioning can be determined; participation in the work of the system of people, machines and the environment; the existence of internal material, energy and information connections between parts of the system, as well as external connections of the system under consideration with other objects. Thus, most production systems are characterized by the fact that they are complex and a person, a manager, a decision-maker is involved in the control circuit. The complexity is manifested in a significant number and variety of parameters of objects that determine the course of various technological and production processes, in a large number of internal connections between the parameters of objects, in their mutual influence, in insufficient knowledge of the properties of systems, and the processes occurring in them, as well as in non-formalized human actions, which are often subjective.

Under these conditions, in the study of production systems in order to build their mathematical models, the problem of uncertainty arises, since the initial information that can actually be collected for the mathematical description of the technological system under study often turns out to be largely incomplete and fuzzy. In addition, production systems are usually difficult to describe quantitatively, since special means for collecting and processing the necessary statistical data in industrial conditions are insufficient, do not have the necessary properties or are absent.

Uncertainty can have a stochastic (probabilistic) nature, when probabilistic hypotheses are fulfilled (axioms of probability theory, statistical stability of the process), or non-stochastic nature, when the initial information is fuzzy, the axioms of probability theory are not fulfilled, and cannot be described in terms of probability theory. Under the conditions of the first type of uncertainty, in the case of the availability of statistical data and the statistical stability of the process, a relatively well-studied and widespread mathematical apparatus of the theory of probability and random processes is used to model the systems under study [4–6].

However, with the development of production, the complication of objects and processes, the increasing role of a person in managing them, uncertainty of the second type often arises, caused by the fuzziness of the initial information. Under these conditions, it becomes necessary to take into account, when describing an object, the characteristics of a person and fuzzy (qualitative, verbal) information received from it. In this paper, let's investigate and the object of management are just such production systems, which, as a rule, are characterized by the indistinctness of the initial information.

The building of a mathematical description of such systems, used in solving problems of decision-making and management, is complicated by the fact that some categories that characterize human activities cannot always be accurately determined, and such uncertainty is not probabilistic, but a different qualitative, fuzzy character. Moreover, in cases where there is reason to believe that objects behave according to probabilistic laws, the lack of information, the lack of statistical data push for other approaches to the description of real production systems and technological processes based on common sense. As already noted, one of these approaches relies on information received from the decision maker, judgments about the functioning of a real object, on the methods of expert assessments and the theory of fuzzy sets [7–12]. The main concepts and elements of the theory of fuzzy sets used in the work are given in the next section.

Let's consider a technological system, the building of a mathematical model and the control of which is difficult, on the one hand, by high a priori uncertainty, lack of data on the course of the technological process, on the other hand, the input and output variables are of a fuzzy nature. However, a person – a decision maker is able to control it, based on a certain model of a qualitative nature, formed in its mind in the process of learning and observing the functioning of the object. It is possible to obtain a formalized model of such an object without resorting to the help of complex mathematical structures, but based on a person's ability to express its essence in fuzzy statements. The simplest model of this type will be the expressions «If we apply to the input of the system $\tilde{x}_i$, then at the output obtain $\tilde{y}_j^M$, where $\tilde{x}_i \in X_i$, $i=\overline{1,n}$; $\tilde{y}_j^M \in Y_j$, $j=\overline{1,m}$, some terms from the term set $T(X_i,Y_j)$, (X_i,Y_j – universal sets), i.e. fuzzy values of linguistic variables». Further, processing the obtained qualitative information by methods of the theory of fuzzy sets, let's obtain a fuzzy model of this object, which can be used to study and control the original system.

The use of the mathematical apparatus of the theory of fuzzy sets makes it possible to build relatively simple and effective models of production systems and algorithms for their control under conditions of uncertainty, when the use of other approaches is impractical or impossible.

Along with the effectiveness of the application of the theory of fuzzy sets, some of its limitations should be noted: the relative complexity of obtaining and systematizing primary qualitative information, the need for additional verification of the reliability of information, the difficulty of choosing fuzzy rules for conditional inference, the complexity of interpretation and building of membership functions, etc. A detailed description of the proposed approach to the synthesis of fuzzy models and the solution of some of the listed problems that arise when using the methods of fuzzy set theory is considered in the following subsections.

1.2 BASIC CONCEPTS AND ELEMENTS OF THE THEORY OF FUZZY SETS

The theory of fuzzy sets is based on the concept of a fuzzy set, which is a mathematical formalization of fuzzy information used in the analysis, modelling, decision-making and management of complex, quantitatively difficult to describe systems. Here are the main provisions and definitions of the theory of fuzzy sets.

Definition 1. Let X – a non-empty set (in the usual sense). A fuzzy set (subset) $\tilde{A}$ on a set $X\left(\tilde{A} \subset X\right)$ is a collection of pairs:

$$\tilde{A}=\left\{x, \mu_{\tilde{A}}(x)\right\}=\int_X \mu_{\tilde{A}}(x)\Big| x,\ \ x \in X,\ \ \mu_{\tilde{A}}(x) \in [0,1].$$

The symbol ∫ denotes the operation of combining one-point fuzzy sets $\mu_{\tilde{A}}(x)\big| x$.

The function $\mu_{\tilde{A}}(x)\, X \to R$, which maps the universal set X in the membership space R, is called the membership function of a fuzzy set $\tilde{A}$. The membership function can be interpreted as a distribution of possibilities. This means that an arbitrary set can be considered as a constraint on the possible values of some variable.

When R contains only two points 0 and 1, $\tilde{A}$ is an ordinary set and its membership function coincides with the characteristic function of the set.

Further, let's assume that R is the interval [0,1], $\mu_{\tilde{A}}(x) = 0$ means that x does not belong to the subset $\tilde{A}$, and $\mu_{\tilde{A}}(x) = 1$ that x does not belong to the subset $\tilde{A}$.

Despite the well-known analogy with the methods of the theory of probability, a significant difference between the methods of the theory of fuzzy sets is that the uncertainty is associated not with randomness, but with the existing inaccuracies and fuzziness.

The carrier of a fuzzy set $\tilde{A}$ is called a set of those elements $x \in X$ for which:

$$\mu_{\tilde{A}}(x) > 0,$$

$$\sup \tilde{A} = \left\{ x : \mu_{\tilde{A}}(x) > 0 \right\}.$$

A fuzzy set $\tilde{A}$ is called normal if the upper bound of its membership function is equal to 1:

$$\sup_{x \in X} \mu_{\tilde{A}}(x) = 1.$$

Otherwise, the fuzzy set is called subnormal.

The equality of the membership function of two fuzzy sets $\tilde{A}$ and $\tilde{B}$, $\mu_{\tilde{A}}(x) = \mu_{\tilde{B}}(x),\ \forall x \in X$ implies the equivalence of these fuzzy sets $\tilde{A} = \tilde{B}$.

Let $\tilde{A}$ and $\tilde{B}$ are fuzzy sets in X. The set $\tilde{A}$ includes $\tilde{B}$, that is $\tilde{B} \subseteq \tilde{A}$, if $\forall x \in X$ satisfied $\mu_{\tilde{B}}(x) \le \mu_{\tilde{A}}(x)$. In this case $\sup p\tilde{B} \subseteq \sup p\tilde{A}$.

On fuzzy sets, it is possible to perform operations similar to those on ordinary sets, as well as perform special operations introduced for using fuzzy sets in decision-making problems. Some operations on fuzzy sets (union, intersection), depending on the specifics of the problem being solved, can be defined in different ways. The choice of a specific type of operation depends on the meaning of these operations.

The classical definitions of union ($\bigcup$) and intersection ($\bigcap$) of sets in the case of fuzzy sets can be written as:

$$\tilde{A} \bigcup \tilde{B} = \left\{ \left\langle \mu_{\tilde{A} \cup \tilde{B}}(x) \middle| x \right\rangle \right\},\ x \in X,$$

where

$$\mu_{\tilde{A} \cup \tilde{B}}(x) = \max\left(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x) \right);$$

$$\tilde{A} \bigcap \tilde{B} = \left\{ \left\langle \mu_{\tilde{A} \cap \tilde{B}}(x) \middle| x \right\rangle \right\},\ x \in X,$$

where

$$\mu_{\tilde{A}\cap\tilde{B}}(x)=\min\left(\mu_{\tilde{A}}(x),\,\mu_{\tilde{B}}(x)\right).$$

The union corresponds to the logical connective «or», and the intersection corresponds to the logical connective «and».

There are other ways of presenting these operations (limited amount, limited work, etc.).

The addition or negation $\tilde{A}$ of a fuzzy set $\tilde{A}\in X$ is a fuzzy set with a membership function:

$$\forall x\in X:\ \mu_{\bar{\tilde{A}}}(x)=1-\mu_{\tilde{A}}(x).$$

Completion operation corresponds to logical negation. For example, fuzzy set $\tilde{A}=\{$quality products$\}$ and $\bar{A}=\{$poor quality products$\}$ are complementary to each other.

The product of fuzzy sets $\tilde{A}$ and $\tilde{B}$ is denoted $\tilde{A}\cdot\tilde{B}$ and determined by the expression:

$$\tilde{A}\times\tilde{B}=\int_X \mu_{\tilde{A}}(x)\mu_{\tilde{B}}(x)\big|x. \tag{1.1}$$

Any fuzzy set A^{α} ($\alpha>0$) based on (1.1) can be written in the form:

$$\tilde{A}^{\alpha}=\int_X \left(\mu_{\tilde{A}}(x)\right)^{\alpha}\big|x.$$

Special cases of the exponentiation operation are the concentrated operation (CON), which reduces the clarity of the set:

$$CON\left(\tilde{A}\right)=A^2=\int_X\left(\mu_{\tilde{A}}(x)^2\big|x\right),\ x\in X$$

and dilatation operation (DIL), increasing the fuzziness:

$$DIL\left(\tilde{A}\right)=A^{0.5}=\int_X\left(\mu_A(x)^{0.5}\big|x\right),\ x\in X.$$

These operations are useful in representing linguistic ambiguities and are used as modifiers (connectives) in fuzzy statements.

The difference between fuzzy sets $\tilde{A}$ and $\tilde{B}$ in X is defined as a fuzzy set A/B with a membership function:

$$\mu_{A/B}(x)=\begin{cases}\mu_{\tilde{A}}(x)-\mu_{\tilde{B}}(x) \text{ at } \mu_{\tilde{A}}(x)\geq\mu_{\tilde{B}}(x),\\ 0 \text{ otherwise.}\end{cases}$$

A symmetric difference is called a fuzzy set $A\nabla B$, which has a membership function:

$$\mu_{A\nabla B}(x)=\left|\mu_{\tilde{A}}(x)-\mu_{\tilde{B}}(x)\right|,\ \forall x\in X.$$

Let $\tilde{A}_1,\ldots,\tilde{A}_n$ – fuzzy sets in $X_1,\ldots,X_n$, respectively. *The Cartesian product* $\tilde{A}_1\times\ldots\times\tilde{A}_n$ of these fuzzy sets in X_i, $i=\overline{1,n}$ is defined as a fuzzy set $\tilde{A}$ in the Cartesian product $X=X_1\times\ldots\times X_n$, with a membership function:

$$\mu_{\tilde{A}}(x)=\min\left\{\mu_{\tilde{A}_1}(x),\ldots,\mu_{\tilde{A}_n}(x_n)\right\},\ x=(x_1,\ldots,x_n)\in X.$$

The set of level $\alpha(A_\alpha)$ – fuzzy set $\tilde{A}\subset X$ is called the usual set of elements that satisfy the condition:

$$\forall\alpha\in[0,1],\ A_\alpha=\left\{x:\ x\in X,\mu_A(X)\geq\alpha\right\}.$$

The set of level α allows to reduce a fuzzy problem to a crisp one and apply known methods to solve the resulting problem. The main properties of the set of level α include:

$$\left(\tilde{A}\cup\tilde{B}\right)_\alpha=\tilde{A}_\alpha\cup\tilde{B}_\alpha;\left(\tilde{A}\cap\tilde{B}\right)_\alpha=\tilde{A}_\alpha\cap\tilde{B}_\alpha;\left(\tilde{A}_1\times\ldots\times\tilde{A}_n\right)_\alpha=\left(\tilde{A}_1\right)_\alpha\times\ldots\times\left(\tilde{A}_n\right)_\alpha;\bigcap_{i=1}^{n}\left(\tilde{A}_i\right)_\alpha\subset\tilde{A}_\alpha.$$

A fuzzy number is a normal fuzzy set defined on the space R^1.

Let universal sets *X, Y* and a mapping *f: X→Y* be given. Let $\tilde{A}$ – some fuzzy subset in *X* with a membership function $\mu_{\tilde{A}}(x)$. According to the *generalization principle* (a way of expanding the domain of definition of mappings to the class of fuzzy sets), the image $\tilde{A}$ under the mapping *f* is defined as a fuzzy subset $\tilde{B}$ of the set *Y* with the membership function given by the relation:

$$\mu_{\tilde{B}}(y)=\frac{\sup}{x\in f^{-1}(x)}\mu_{\tilde{A}}(x),$$

moreover, the maximum is taken over all points that make up the preimage:

$$f^{-1}(y)=\left\{x:\ x\in X;f(x)=y\right\}.$$

The image $\tilde{B}$ of a *fuzzy set* $\tilde{A}$ in *X* with a fuzzy mapping $\mu_f X\times X\to[0,1]$ – a fuzzy set with a membership function:

$$\mu_{\tilde{B}}(x)=\sup_{x\in X}\min\left\{\mu_{\tilde{A}}(x),\ \mu_{\tilde{B}}(x,y)\right\}.$$

Generalization principle algorithm. The generalization principle allows to find the membership function of a fuzzy number corresponding to the value of a crisp function of fuzzy arguments. Computer-oriented implementation of the fuzzy generalization principle is carried out according to the following algorithm:

Step 1. Fix the value $y=y^*$.

Step 2. Find all $x_n\ [x^*_{1,j},x^*_{2.j},\ldots,x^*_{n,j}],\ j=\overline{1,k}$, satisfying the conditions $y^*=\left(x^*_{1,j},x^*_{2,j},\ldots,x^*_{n,j}\right)$ and $x^*_{i,j}\in\sup p\left(\tilde{x}_i\right),\ i=\overline{1,n}$.

Step 3. The degree of membership of the element y^* to a fuzzy number $\tilde{y}$ is calculated by the formula:

$$\mu_{\tilde{y}}\left(y^*\right)=\max_{j=\overline{1,k}}\min_{i=\overline{1,n}}\left(\mu_{\tilde{x}_i}\left(x_{i,j}^*\right)\right).$$

Step 4. Check the condition «Are all elements of y taken?» If yes, then go to Step 5. Otherwise, fix the new y^* value and go to Step 2.

Step 5. End.

The given algorithm is based on the representation of a fuzzy number on a discrete universal set, i.e.

$$\tilde{x}=\sum_{p=1}^{P}\mu_{\tilde{x}}\left(x_p\right)/\,x_p.$$

Usually the initial data $\tilde{x}_i,\ i=\overline{1,n}$ are set by piecewise continuous membership functions:

$$\tilde{x}_i=\int_{x_i\in R}\mu_{\tilde{x}i}\left(x_i\right)/\,x_i.$$

To calculate the values of the function $\tilde{y}=f\left(\tilde{x}_1,\tilde{x}_2,\ldots,\tilde{x}_n\right)$, the arguments $\tilde{x}_i,\ i=\overline{1,n}$ are discretized, i.e. are represented in the form:

$$\tilde{x}_i=\sum_{p=1}^{P}\mu_{\tilde{x}i}\left(x_{i,p}\right)/\,x_{i,p}.$$

The number of points P is chosen so as to provide the required accuracy of calculations. The output of this algorithm is a fuzzy set, also given on a discrete universal set. The resulting piecewise continuous membership function of a fuzzy number $\tilde{y}$ is obtained as the upper envelope of points $\left(y^*,\,\mu_{\tilde{y}}\left(y^*\right)\right)$.

Definition 2. A fuzzy mapping $f: X\rightarrow Y$ of a set X into a set Y is a fuzzy subset with a given membership function $\mu_{\tilde{f}}\left(x,\,y\right)$.

A fuzzy mapping $\tilde{f}$ can be defined not only on X, but also on a collection of fuzzy subsets of X (a fuzzy subalgebra $F(X)$). If $\left\{\tilde{A},\,\mu_{\tilde{A}}\left(x\right)\right\}\in F\left(X\right)$, then:

$$\mu_{\tilde{f}(A)}\left(y\right)=\max_{x\in X}\left[\min\left(\mu_{\tilde{A}}\left(x\right),\,\mu_f\left(x,\,y\right)\right)\right].$$

When modelling and managing complex objects based on the methods of the theory of fuzzy sets, one of the most common mathematical concepts is the concept of a fuzzy relation. The importance of this concept lies in the fact that it, on the basis of expert information, allows to formulate and analyze mathematical models of complex systems.

Definition 3. A fuzzy relation R on a set X is a fuzzy subset of the Cartesian product $X\times X$, which is characterized by the membership function $\mu_R:\ X\times X\rightarrow[0,1]$. *The value* $\mu_R\left(x,x\right)$ of this function is understood as a subjective measure or degree of fulfillment of the relationship xRx.

An ordinary relation can be viewed as a special case of a fuzzy relation, the membership function of which is 0 or 1.

In general, the relation R is a fuzzy subset of the Cartesian product:

$$R = \int_{X_1 \times \ldots \times X_n} \mu_R(x_1, \ldots, x_n) \big| (x_1, \ldots, x_n).$$

Here are the main characteristics of fuzzy relations.

The carrier of a fuzzy relation R on a set X is a subset of the Cartesian product $X \times X$:

$$\sup pR = \{(x,y) : (x,y) \in X \times X, \mu_R(x,y) > 0\}. \tag{1.2}$$

It is seen from (1.2) that sup pR connects all pairs (x, y) for which the degree of fulfillment of a given fuzzy relation is not zero.

The set of the level α of fuzzy relations R is determined by the formula:

$$R_\alpha = \{(x,y) : (x,y) \in X \times X, \mu_R(x,y) \geq \alpha\}.$$

Let's consider operations on fuzzy relations, some of which are analogs of operations on fuzzy sets, and some of which are inherent only in fuzzy relations.

Let two fuzzy relations A and B be given on X. Fuzzy relations $A \bigcup B$ and $A \bigcap B$ are called the *union* and *intersection* of fuzzy relations A and B on X with a membership function:

$$\mu_{A \cup B}(x,y) = \max\{\mu_A(x,y), \mu_R(x,y)\}, \ \mu_{A \cap B}(x,y) = \min\{\mu_A(x,y), \mu_R(x,y)\}.$$

The addition of a fuzzy relation $R \subset X$ is a relation $\overline{R}$ with a membership function:

$$\mu_{\overline{R}}(x,y) = 1 - \mu_R(x,y), \ \forall x, y \in X \times X.$$

The inverse of R the fuzzy ratio of R^{-1} to X is defined:

$$xR^{-1}y \Leftrightarrow yRx, \ \forall x, y \in X \ \text{ or } \mu_{R^{-1}}(x,y) = \mu_R(x,y), \ \forall x, y \in X.$$

The algebraic sum and the product of fuzzy relations $\tilde{A}$ and $\tilde{B}$ are given, respectively, by the membership function:

$$\mu_{A+B}(x,y) = \mu_A(x,y) - \mu_B(x,y) - \mu_A(x,y) \times \mu_B(x,y), \ \mu_{A \times B}(x,y) = \mu_A(x,y) \times \mu_B(x,y).$$

Composition (product) of fuzzy relations, which can be defined in various ways, is of great importance in modelling and decision-making problems. The most frequently used definitions of this operation are *maximin and minimax compositions*, characterized, respectively, by the membership function:

$$\mu_{A\times B}(x,y)=\sup_{z\in X}\min\{\mu_A(x,y),\,\mu_B(z,y)\},$$
$$\mu_{A\times B}(x,y)=\inf_{z\in X}\max\{\mu_A(x,y),\,\mu_B(z,y)\}.$$

The next fundamental concepts used in fuzzy set theory are fuzzy and linguistic variables.

Definition 4. A fuzzy variable is a set $<F,X,R(F;\,x)>$, where F – the name of a fuzzy variable, $X=\{x\}$ – a universal set that determines the range of F, $R(F;\,x)\subseteq X$ – a fuzzy set, which is a *fuzzy constraint* on the values of the variable F, the variable U is the base variable for F.

The fuzzy variable F is characterized by an *assignment equation* of the form:

$$f=x,\ \ x\in R(F;x). \tag{1.3}$$

This equation reflects that the variable f is assigned the value x subject to the constraint $R(F;\,x)$.

The degree to which equality (1.3) is satisfied is called the *compatibility of the value* of x with $R(F;\,x)$ and is denoted by $C(x)$:

$$C(x)=\mu_{R(F;x)}(x),\ x\in X,$$

where $\mu_{R(F;x)}(x)$ – degree of membership in the constraint $R(F;\,x)$, which is a measure of how much the value of x satisfies the constraint $R(F;\,x)$.

Now let's move on to considering a linguistic variable, which is a variable of a higher order than fuzzy. This is determined by the fact that the values of the linguistic variable are fuzzy variables. For example, the values of the linguistic variable *quality* can be: «low», «medium», «not high», «high», «very high», etc. Each of these values is the name of a fuzzy variable.

From the above example, it can be seen that the values of a linguistic variable are not numbers, as in a numeric variable, but a word or a sentence in a natural or formal language. This property of a linguistic variable makes it possible to approximately describe complex, quantitatively difficult to describe systems and phenomena in a familiar or natural language.

The following two rules are used to describe the *structure* of a linguistic variable:

– *syntactic*, which is set in the form of a grammar that generates the names of the values of the variable;

– *semantic*, which defines an algorithmic procedure for calculating the meaning of each value.

Let's give a formal definition of the concept of a linguistic variable.

Definition 5. A linguistic variable is characterized by a set (L, $T(L)$, U, G, M), in which L – name of the variable; $T(L)$ – set of its values, i.e. *term-set* of variable L, and each linguistic value L is a fuzzy variable F with values from the universal set X with base variable x. The set $T(L)$ will be called the base term-set of the linguistic variable; G is a syntactic rule (in particular, a formal grammar) that describes the process of forming new values of a linguistic variable (the name of a fuzzy variable *F*) based on its term set. The sets $T^* = T \bigcup G(T)$ will be called the *extended term-set* of the linguistic variable; *M* is a semantic rule that assigns to each fuzzy variable *F* its meaning *M*(*F*), i.e. a fuzzy subset *M*(*F*) of the universal set *X*. The semantic procedure *M* (for example, an expert survey) allows to transform each new value of a linguistic variable. Formed by the procedure *G*, into a fuzzy variable, i.e. to ascribe semantics to it by forming the corresponding fuzzy set.

A term is a specific name F generated by a syntactic rule *G*. *A term-set* is defined by the union of terms.

The meaning *M*(*F*) of the term *F* can be defined as the constrain of *R*(*F*; *x*) to the base variable x, due to the fuzzy variable *F*:

$$M(F)=R(F;\,x). \tag{1.4}$$

In (1.4), the fuzzy constrain *R*(*F*; *x*) and, therefore, the meaning of *M*(*F*) can be regarded as a fuzzy subset of the universal set *X*, which is called *F*.

The assignment equation in the case of a linguistic variable takes the form:

F-term in *T*(*L*) = name generated by grammar *G*. (1.5)

Substituting (1.5) into (1.4), let's define the meaning of the term *F* in the form *M*(*F*) = *R* (the term in *T*(*L*)).

An axiomatic approach to determining the fuzziness index of a fuzzy set. The fuzziness index of a fuzzy set can be defined as a measure of the internal uncertainty, ambiguity of objects of the set *x* with respect to some property *A*, which characterizes these objects and defines a fuzzy set of objects *A* at *x*. If some object $x \in X$ has property *A*, but only to a partial extent: $0 < \mu_A(x) < 1$, then the internal uncertainty, the ambiguity of the object *x* in relation to property *A* is manifested in the fact that it, although to varying degrees, belongs to two opposite classes at once: the class of objects «possessing property *A*» and the class of objects «not possessing the property BUT». This ambiguity of the object x in relation to property *A* is maximal when the degrees of belonging of the object *x* to both classes are equal, i.e. $\mu_A(x) = \mu_{\bar{A}}(x) = 0.5$. Conversely, the ambiguity of an object is minimal when the object belongs to only one of these classes, i.e. or $\mu_A(x) = 1, \mu_{\bar{A}}(x) = 0$ either $\mu_A(x) = 0, \mu_{\bar{A}}(x) = 1$. Thus, the global fuzzy index of a fuzzy set *A* can be defined as a functional d satisfying the following conditions:

P1. $d(A) < d(B)$, if *A* is a sharpening of *B*, i.e. $\mu_A(x) \le \mu_B(x)$ at $\mu_B(x) < 0.5$, $\mu_A(x) \ge \mu_B(x)$ at $\mu_B(x) > 0.5$ and $\mu_A(x)$ – any at $\mu_B(x) = 0.5$;

P2. $d(A) = d(\bar{A})$;

P3. If $A \bigcap B = \varnothing$, то $d(A \bigcup B) = d(A) + d(B)$.

So, the fuzzy exponent can be considered as an additive, symmetric and strictly increasing with increasing fuzzy set, a functional defined on the set $\Im(X)$ of all fuzzy subsets of the set *x*.

Metric approach to determination of fuzzy set fuzzy index. The fuzzy index of fuzzy sets can be determined using a metric as a measure of the difference between a fuzzy set and the nearest ordinary set. Another way to define the fuzzy metric using a metric is to determine it using the distance to the maximum fuzzy set $A_{0.5}: \ \forall x \in X \mu A_{0.5}(x) = 0.5$ and the distance between the fuzzy set and its complement. It turns out that these approaches have a lot in common, and the fuzziness index determined using the metric has set of the properties formulated above.

The set closest to a fuzzy set A is a crisp set A such that:

$$\mu_{\underline{A}}(x) = \begin{cases} 1, \text{ if } \mu_A(x) > 0.5; \\ 0, \text{ if } \mu_A(x) \le 0.5. \end{cases}$$

The fuzziness indicator is called the functional:

$$d(A) = \frac{2}{N} \sum_{j=1}^{N} \left| \mu_A(x_j) - \mu_{\underline{A}}(x_j) \right|,$$

which can also be represented as:

$$d(A) = \frac{2}{N} \sum_{j=1}^{N} \mu_{A \cap \bar{A}}(x_j).$$

If, instead of the Hamming distance, let's use the Euclidean distance, then:

$$d(A) = \frac{2}{\sqrt{N}} \sqrt{\sum_{j=1}^{N} \left(\mu_A(x_j) - \mu_{\underline{A}}(x_j) \right)^2}.$$

The fuzziness factor can be set using the distance between the fuzzy set and its complement:

$$d(A) = k\left[\rho(\varnothing, U) - \rho\left(A, \bar{A}\right) \right].$$

In the case of the Hamming metric $\rho\left(A, \bar{A}\right)$, it has the form:

$$\rho\left(A, \bar{A}\right) = \sum_{j=1}^{N} \left| \mu_A(x_j) - \mu_{\bar{A}}(x_j) \right| = \sum_{j=1}^{N} \left| 2\mu_A(x_j) - 1 \right|.$$

This fuzziness index satisfies the properties of P1 and P2.

Next, let's find out that a one-to-one correspondence can be established between the fuzziness indices satisfying the conditions P1, P2, P3, and the metrics of a certain class.

Superadditive measures. Belief function. The definition of the belief function assumes that the belief degree in the statement A, which is true, does not necessarily equal 1. This means that the sum of the belief degrees in the statement A and its negation A is also not necessarily equal to 1, but can be either equal or less than 1. Others in words, when statement A is true to a certain degree $s \in [0,1]$, its measure of uncertainty is expressed using the function:

$$b(B) = \begin{cases} 1, \text{ if } B = X; \\ s, \text{ if } B \supset A, B \neq X; \\ 0, \text{ if } B \not\subset A, \end{cases}$$

which is called a simple carrier function centered on A.

If $s=1$, then let's obtain a measure, which is called the measure of definiteness concentrated on A.

If $s=0$ or $A=X$, then $b(B)$ is called an empty belief function (complete ignorance).

So, a belief function is a measure that satisfies the following properties:

1. $b(\varnothing) = 0;$
2. $b(X) = 1;$
3. $\forall\ A \in \wp,\ 0 \le b \le 1;$
4. $\forall A_1,\dots,A_n \in \wp,\ b(A_1 \cup \ldots \cup A_n) \ge \sum_{i=1}^{n} b(A_i) - \sum_{i<j} b(A_i \cap A_j) + \ldots + (-1)^{n+1} b(A_1 \cap \ldots \cap A_n).$

Consistent belief function. The concept of a consistent belief function is based on the definition of a fully nested nesting core $C = \{B \subset X \mid m(B) > 0\}$.

An agreed unbelieved function is defined using the following axioms:

1. $b(\varnothing) = 0;$
2. $b(X) = 1;$
3. $b(A \cap B) = \min\{b(A), b(B)\}.$

Subadditive measures. Likelihood measure. The likelihood measure of a set A from X is defined as $Pl(A) = 1 - b(\bar{A})$, where b – belief function.

The likelihood measure satisfies the following axioms:

1. $Pl(\varnothing) = 0;$
2. $Pl(X) = 1;$
3. $\forall A_1,\dots,A_n \subseteq X,\ Pl(A_1 \cap \ldots \cap A_n) \le \sum_{i=1}^{n} Pl(A_i) - \sum_{i<j} Pl(A_i \cup A_j) + \ldots + (-1)^{n+1} Pl(A_1 \cup \ldots \cup A_n).$

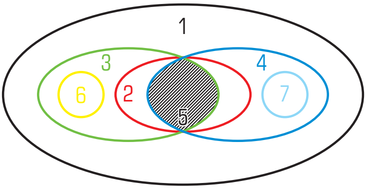
Let μ and ν be two measures such that $\forall A \in \wp\ \ \mu(A) + \nu(\bar{A}) = 1$. In this case, μ is a belief function if and only if ν is a likelihood measure.

A measure of opportunity. The measure of possibility is a function $\Pi\colon\ \wp \to [0,1]$ that satisfies the following axioms:

1. $\Pi(\varnothing) = 0;$
2. $\Pi(X) = 1;$
3. $\forall i \in N,\ A_i \subset X,\ \Pi\left(\bigcup_{i \in N} A_i\right) = \sup_{i \in N} \Pi(A_i).$

Let μ and ν be two measures such that $\forall A \in \wp\ \ \mu(A) + \nu(\bar{A}) = 1$. A fuzzy measure μ is a consistent belief function if and only if ν is a measure of possibility.

Probability measure. A probabilistic measure $(\lambda = 0)$ is a special case of a belief function or a likelihood measure (**Fig. 1.1**).



1 – fuzzy measures;
2 – q_ν-measures;
3 – *trust functions*;
4 – *likelihood measures*;
6 – *consistent trust functions*;
7 – *measure of opportunity*

Fig. 1.1 Relationships between different measures

A fuzzy measure p is a probability measure if and only if the following conditions are met:

$$\rho(\varnothing) = 0;\ \rho(X) = 1;$$

$$\forall i \in N,\ A_i \subset X,\ \forall i \le j\ \left(A_i \cap A_j = \varnothing \Rightarrow \rho\left(\bigcup_{i \in N} A_i\right) = \sum \rho(A_i)\right).$$

A fuzzy measure q_ν is called q_ν – a measure if it satisfies the following axioms:

$$q_\nu(\varnothing) = 0;\ q_\nu(X) = 1;$$

$$\forall i \in N,\ A_i \in \wp,\ \forall i \ne j\ A_i \cap A_j = \varnothing \Rightarrow q_\nu\left(\bigcup_{i \in N} A_i\right) = (1 - v) \bigvee_{i \in N} q_\nu(A_i) + \nu \sum_{i \in N} q_\nu(A_i),\ \nu \ge 0;$$

$$\forall A, B \in \wp\ (A_i \subseteq B \Rightarrow q_\nu(A) \le q_\nu(B)).$$

1.3 TYPES AND SOURCES OF UNCERTAINTY IN THE STUDY OF PRODUCTION SYSTEMS AND WAYS TO REDUCE UNCERTAINTY

Most of the production systems in which various processes take place, a person participates, they function under conditions of uncertainty. This uncertainty arises for a number of reasons, the main ones being:

– the complexity of the production facility and system, insufficient knowledge of the processes taking place in it;

– the stochastic nature of the main parameters describing the functioning of a technological system, a production facility;

– the presence of a large number of disturbing influences and interference in production, information noise;

– insufficient reliability of the initial statistical information due to low reliability, lack or absence of industrial means for collecting and processing such information;

– disadvantages of information processing methods;

– poorly formalized actions of a person participating in the control loop, and the subjectivity of its actions when making decisions;

– vagueness, qualitative nature of the information collected from experts, describing the state of the system, production facility;

– the presence of fuzzy constraints and criteria in the optimization and management of production facilities and processes.

Thus, the main sources of uncertainty in the production environment are insufficient and fuzzy initial information.

Depending on the nature of the occurrence and the source, the following two groups of uncertainty can be distinguished [2, 13]:

1. Uncertainty characterized by a probabilistic nature. It arises when technological parameters for which probabilistic hypotheses are fulfilled are described by random values. The formalization tool is the mathematical apparatus of the theory of probability and random processes [4, 6, 7].

2. Uncertainty, which is characterized by indistinctness, qualitative nature of the initial information. Here the state of the object is described by fuzzy values and linguistic variables expressed by the decision maker. As a means of formalizing and processing fuzzy information, in these cases, the methodology of the theory of fuzzy sets is used [11, 12, 14].

Let's note that the hypotheses of the theory of probability are often not fulfilled for production facilities in which a special role in management belongs to humans. Consequently, there is an uncertainty of type 2, formalized on the basis of the methods of the theory of fuzzy sets.

The problem of lack of information, the sources of which were considered in the previous subsection, can be solved on the basis of the following approaches [2, 11, 15]:

– the lack of information is reduced due to additional activities and costs;

– tries on the lack of information and continues research in the current conditions.

The lack of information can be attributed not only to its insufficient amount, its inaccuracy, which devalues the available information, but also the fuzzy (qualitative) nature of a part of the information, which complicates its formalization and processing. The information deficit can be reduced in various ways, depending on what is causing it [16]. Inaccuracy can arise at the stage of information gathering, when any values are distorted due to measurement errors or due to an incorrect assessment by an expert. Such errors can be corrected by increasing the cost of the measurement, for example, by improving the measurement tools, by repeating measurements or by additional expert interviews.

One has to put up with a lack of information if the costs of reducing it are high, there is not enough time to obtain additional reliable information, or it is impossible to obtain such information.

Methods of processing can have a significant impact on the quality of information. Here the problem of lack of information may arise due to the shortcomings (incompleteness) of the object model or methods of its processing. In this case, it is possible to try to supplement the existing model by including unaccounted factors or build other models, for example, based on taking into account additional fuzzy information, and adopt more expedient methods of information processing. Reconciliation with the lack of information here is also determined by the permissible costs, the allotted time and the baggage of knowledge.

Attempts to extend traditional modelling methods to complex objects (production systems, technological complexes, etc.) have not yet yielded significant results in practice, despite the significant development of mathematical methods and computer technology. In practice, such objects and processes are managed quite well by a person (decision maker, operator). In such cases, a person quite successfully copes with the uncertainty and complexity of the management process, using fuzzy, qualitative concepts, successfully navigates in a difficult environment. In this regard, the problem arises: how to transfer human abilities to a computer for modelling and controlling complex industrial objects and technological processes. To solve such a problem, special methods of obtaining, formalizing and processing fuzzy information, the source of which is a person (specialist-expert, decision maker), are required. In the following subsections, let's discuss the main methods for solving these problems.

1.4 TECHNOLOGICAL FACILITIES OF OIL REFINING PRODUCTION, MAIN CHARACTERISTICS AND ISSUES OF INCREASING THE EFFICIENCY OF THEIR OPERATION

Various technological processes of oil refining take place in specially designed technological units. Final petroleum products are usually obtained in a complex of such technological units, which includes various interconnected units, for example, furnaces, reactors, distillation columns, heat exchangers, etc. Such a complex of oil refining production is called a technological unit. Thus, oil refining is a set of physical and physical and chemical processes carried out at technological units of oil refineries, including the processes of preparing crude oil for processing, primary and deep processing of oil and oil products.

The issues of effective management of technological processes of oil refining and their optimization according to many criteria on the basis of mathematical models have recently become very relevant. In this regard, research work has intensified aimed at solving them. A significant contribution to the development of optimization of the technology of oil refining and petrochemistry was made by Russian scientists: V. Kafarov, I. Kolesnikov, V. Meshalkin and others. Among Kazakhstani scientists in this direction are known the works of T. Serikov and R. Sarmurzina, B. Orazbaev and its students L. Kurmangazieva, Ye. Ospanov, B. Utenova and others have obtained important results on the development and application of mathematical methods and computer technology in solving production problems of oil refining.

Various petroleum products and petrochemical raw materials are obtained from petroleum refining. The main types of petroleum products include: automobile and aviation gasolines, diesel fuel, gas oil, heating oil, fuel oil, tar, petroleum coke, gas and others, which are produced in various brands and grades [17].

For effective research and optimization of oil refining processes and units, it is necessary to build their mathematical models, which take into account the nature and state of the process, the type, nature and other features of the objects. For this purpose, it is necessary to classify the technological processes and units of the oil refining industry. Let's consider this classification and their features.

All processes of chemical technology, including oil refining, can be subdivided into two large classes, physical and physicochemical [18].

Physical ones include those in the course of which there is no change in the composition of the processed raw materials, for example, such are the processes of oil distillation and gas fractionation, oil purification with selective solvents and absorbents, extraction processes from oil fractions of various groups of hydrocarbons with selective solvents.

Physical and chemical processes of processing and gas, oil fractions and processes of chemical and petrochemical synthesis are characterized by a change in the composition and structure of molecules with the formation of qualitatively new compounds. Physicochemical processes in industry are divided into thermal, thermocatalytic and radiation-chemical.

Thermal processes include pyrolysis and thermal cracking of oil fractions and gases, oxidation and chlorination of paraffins and olefins, sintering processes, coking and others.

Thermocatalytic processes are most widely used in industry for the upgrading of raw material and the production of various valuable products from petroleum and chemical raw materials. These processes include catalytic cracking, catalytic reforming, hydrotreating, hydrocracking, and others. With the help of thermocatalytic processes, cracking of petroleum raw material is carried out in the presence of various catalysts, isomerization of paraffinic, aromatic and olefinic hydrocarbons in the presence of gamma alumina containing platinum or in the presence of other catalysts; reforming of low-octane gasolines into high-octane ones on catalysts and others [19–24].

Thermocatalytic processes in industrialized countries make it possible to receive up to 1/5 of the national income. In the oil refining industry, over 70 % of oil is processed using catalytic processes.

All considered processes take place in technological units. These units are selected by calculation and are connected according to a certain scheme, creating various technological units. Let's consider the classification of the main technological units of oil refining [25–28].

Units for primary oil refining include ELOU-AT-2 and ELOU-AVT units.

The ELOU-AT-2 direct distillation unit is designed for the primary oil refining process. The ELOU (electrical desalting) section is intended for oil preparation by electrical desalting and dehydration in an electric field, and the AT (atmospheric-tubular) section of the unit is intended for separating demineralized and dehydrated oil into separate fractions by heating it, evaporating, fractionating and condensing distillate vapors.

The ELOU-AVT unit (atmospheric vacuum tubular) is designed for oil treatment at an electrical desalting unit and processing at atmospheric and vacuum units.

Units for carrying out thermocatalytic processes include a catalytic reforming unit. The catalytic reforming unit is designed to produce a high-octane component of automobile and aviation gasolines and hydrogen-containing gas.

The units for deep oil refining include units for delayed coking and units for calcining petroleum coke, in which thermal processes take place.

The delayed coking unit is designed to produce petroleum coke, which serves as a raw material for the electrode industry. In addition to the target product – petroleum coke, the unit produces heating oil, heavy gas oil and wet gases.

The petroleum coke calcination unit is designed to remove volatile components and moisture, and obtain calcined coke that meets the requirements.

The complexity of the technology for processing hydrocarbon raw materials determines the need to involve mathematical models and computer technology in the design of processes and control of their operation. The creation of a mathematical model of the process is a very laborious work and is associated with the implementation of a large amount of research work. When creating a model, work is carried out at various levels of complexity, which are distributed depending on the problem, experience, equipment and information content.

In the beginning, as a rule, the type of process is distinguished, attributed to the appropriate class, and research is carried out to identify the patterns of the process. For a given process, various thermodynamic, heat engineering, kinetic and other calculations and experimental studies are performed. In this case, it is necessary to identify the relationship between input and output, internal and external variables of the process. Then, if possible, develop theoretical ideas about the process and its course. On the basis of experimental and theoretical studies, a mathematical model of the process is drawn up.

Based on the data of the enlarged (pilot) unit, taking into account the type of process and on the basis of information from experts, mathematical models are specified and the adequacy of the model to the original is determined. In connection with the enlargement of the scale and the increased consumption of raw materials, catalyst and other types of costs, the processes in this case tend to be carried out in rational, close to optimal ones, which were identified at the previous stages of the study. This reduces energy and other costs without sacrificing the value of the information obtained about the operation of the process plant.

Features and economic, ecological and other characteristics of the main processes of oil refining are considered in many works, for example, in [29]. Basically, Kazakhstani oil refineries are built according to the scheme of two technological processes [29]. The first, simplified process, includes a crude oil distillation unit, a reforming unit, and a distillate hydrotreating unit. The second process is a residue processing complex. It includes units for vacuum distillation, gas oil hydrotreating, catalytic cracking and gas fractionation unit. At the Pavlodar refinery, the catalytic cracking complex is in operation, but at the Shymkent refinery it is not completed and work is currently underway to complete this project. Atyrau and Pavlodar refineries have delayed coking units and coke calcination units.

Processes such as hydrocracking, alkylation, catalytic polymerization, demercaptanization are absent at oil refineries in Kazakhstan. To date, the refining depth at the Atyrau and Shymkent refineries is 70 %, and at Pavlodar – 76 %. The main immediate goal of the existing refineries of the republic is further measures to increase the depth of processing, modernize existing equipment, improve environmental friendliness and optimize production.

A common feature of the republic's oil refineries is the lack of modern equipment. There are practically no automated process control systems. At the Shymkent Refinery, work has begun on the implementation of Automated Process Control Systems (APCS), in the Atyrau Refinery, several Automated Workstations (AWS) have been introduced for plant operators working in the advisor mode.

Another common feature of the republic's oil refineries is the high energy consumption and the lack of measures taken in the field of environmental protection. So, at the Atyrau refinery there is no desulfurization process, oil waste is buried directly on the territory of the refinery.

Environmental issues for oil refining enterprises are very relevant. This is explained by the outstripping development of production volumes in this industry in comparison with the improvement of environmental protection measures, the appearance of hard-to-dispose, and in some cases ballast products – production waste, a change in the range of oils – the appearance of sulfurous and high-sulfur oils and gas condensate, as well as other reasons, the elimination of which requires technical solutions and significant capital costs [30–34].

Modern oil refining facilities are characterized by a high concentration of potential hazards. Every year in the world at oil refineries there are about 1,500 accidents, the material damage from which is on average over 100 million USD per year, and the level of accidents tends to grow [31].

The main types of hazards in the industrial territory of oil refining facilities are fires, gas pollution and explosions. According to statistics, fires account for 58.5 % of the total number of accidents, gas pollution – 17.9 %, explosions – 15.1 %, other emergencies – 8.5 %. The danger of gas contamination of the industrial territory of oil refining facilities is associated with the formation of fields (zones) of concentrations of saturated hydrocarbons exceeding the established maximum permissible values and reaching the lower concentration limit of flame propagation both in a possible accident and in the normal (regulations) mode of operation of technological equipment [32, 33].

The most effective way to solve the problems of gas contamination of oil refining production in the study and forecasting of the dispersion of harmful and explosive substances is the use of methods of mathematical modelling. Many studies are devoted to this issue [34–40]. However, a very limited number of models can be used to calculate the fields of emergency gas contamination of the industrial territory of oil refining facilities in connection with the specifics of production, substances used in technology, terrain and meteorological conditions. The building of the necessary mathematical models is also complicated by the fact that there is a problem of lack and lack of clarity of the initial information.

Therefore, for a specific potentially hazardous enterprise, it is necessary to analyze and build mathematical models that allow taking into account the specifics of a possible accident, local meteorological conditions and the vagueness of the initial information. With the help of these models, estimates of the parameters of gas contamination zones and their danger are calculated both for the object of research itself and for the nearest ones, incl. and residential areas.

According to the existing regulatory requirements, the industrial territory of open technological units of oil refining is equipped with automatic gas analyzers-signaling devices, the range of production of which is quite wide all over the world [41, 42]. The general disadvantages of emergency protection systems containing such devices in their basis are: the small channel of a separate gas analyzer and, in this regard, a large number of secondary devices; low information content; impossibility of predicting the danger of emergency gas contamination; lack of self-diagnosis; lack of control over the serviceability of operation of protection systems; lack of fixation of emergency modes (date, time, place, reason, etc.) in case of gas contamination or malfunction.

The noted shortcomings are largely eliminated during the design and implementation of automated complexes of explosion, fire, emergency protection (AC EFEP) at oil refining facilities, the functional diagram, which is developed in Section 5 of this work.

Foreign companies produce systems of this type, for example, the Cafety Review system (Riken Keiki Co., LTD, Japan) and Safer (Safer Energency Systems Inc., Co, USA) [43, 44]. However, these systems do not use the ability to predict the danger of emergency gas contamination and the ability to control protective equipment. Currently, considerable experience has been accumulated in the design, unit and operation of automated control systems for technological processes of fire protection (ACS TP FP) [45], automated air pollution control systems (ACS AP) [46], which should be used in the development of system-wide solutions and descriptions organizational and technical support of AC EFEP. These works [44, 46] also consider the issues of rational placement of sensors for monitoring emergency gas contamination included in the complex of technical means of AC EFEP on the industrial territory of technological units of oil refineries, and algorithms for solving these problems.

The economic feasibility of clustering industrial enterprises of oil refining and petrochemicals (in the Atyrau region of the Republic of Kazakhstan) leads to the creation of industrial complexes in which the main technological units are located close to the city and the settlement. In addition, due to the creation of high-intensity technological processes for the processing of oil and gas, as well as units of large unit capacity, fundamentally new requirements have arisen both for the creation of these industries and for their location, namely:

– ensuring a high degree of reliability of their functioning in order to avoid accidental emissions of harmful substances into the environment;

– organization of optimal work by mathematical modelling of the technological complex, taking into account the aggregate economic and environmental requirements [47];

– optimal distribution of loads across apparatuses, reactors, etc., ensuring the most complete regeneration of energy flows and efficient use of material resources in order to fully utilize all possible emissions of harmful substances into the environment.

Recently, sufficient attention has been paid to the issues of intensification of the oil refining industry on the basis of mathematical methods (modelling and optimization). However, most of the studies are devoted to the consideration of production, technological and economic and environmental issues of individual technological processes, modernization of specific units, disposal of certain environmentally harmful components, etc. An effective solution to the problem requires an integrated approach to the entire cycle of oil refining, including the storage and processing of oil and oil products, an increase in the depth of processing, and the production of secondary products from the waste of the main production. It is advisable to consider the oil refining industry as a single system in the composition of subsystems: preparation for cleaning, primary and deep processing, storage and sale of oil products. In all these subsystems, it will be necessary to take into account economic, environmental and technological criteria of work efficiency, as well as to use modern achievements of mathematical methods and computer technology. As a result, the methods of mathematical modelling and optimization of technological objects of oil refining, developed in this monograph, are assumed to be extremely important and relevant.

A rational method for cleaning and refining oil must be selected taking into account the following economic and environmental criteria [48–52]:

– minimization of the prime cost of the main products, the use of minimal sites for unit, the use of inexpensive and non-scarce reagents;

– possibility of direct use of end products or their convenient processing;

– full automation of the process in the cleaning plant and flexibility to possible fluctuations in modes;

– the minimum amount of sulfur compounds in the gases emitted from the unit, ensuring good dispersion in the atmosphere;

– the optimal operating mode of technological units based on mathematical modelling and effective decision-making.

1.5 CHOOSING THE DIRECTION OF RESEARCH – METHODS OF MATHEMATICAL MODELLING AND DECISION-MAKING IN THE MANAGEMENT OF TECHNOLOGICAL FACILITIES ACCORDING TO ENVIRONMENTAL AND ECONOMIC CRITERIA

At present, with the development of science, technology and production, oil refining technological facilities, like other production facilities, are continuously becoming more complex, and even now they are talking about these objects as some kind of complex system that consists of various components interconnected with each other and characterizing a set of criteria economic, ecological character [53, 54]. Therefore, the methods of multi-criteria optimal decision-making on control based on system modelling, proposed in this research work, are the most effective and promising methods of research and solving production problems of oil refining.

When applying the methods of systematic mathematical modelling of technological systems of oil refining, it is necessary, first of all, to clearly define the purpose of modelling. Since it is impossible to completely simulate a really functioning system – the investigated technological unit of oil refining (original system), a mathematical model (system-model) is created for the problem posed. Thus, in relation to modelling issues, the goal arises from the required modelling problems, which allows to approach the choice of criterion and assess which elements will be included in the created model.

The set of elements and connections between them allows to judge the structure of the system. In the mathematical description of the production system, individual functions are considered, i.e. algorithms of system behavior. Such a description of the structure is realized when using a functional approach that evaluates the functions that the system performs, and the function is understood as a property that leads to the achievement of the goal. In the presence of some reference standard, it is possible to enter the quantitative and qualitative characteristics of the systems. For a quantitative characteristic, numbers are introduced that express the relationship between this characteristic and the standard. The qualitative characteristics of the system are found, for example, using the methods of expert assessments [55–57] and the theory of fuzzy sets [58–62].

In a production environment, experts often find it difficult to assess the situation, dependence, influence of parameters quantitatively, even using scales. In such cases, it is necessary to conduct an expert assessment in a fuzzy environment, i.e. high-quality expertise, but in the scientific literature this area is poorly studied and there are no methods for organizing and conducting such an expert procedure. The method proposed by the authors for solving this problem [63] is described in the next section.

A model is a material object or an ideal (in the sense of reflecting reality) copy of the original object, which is so similar to it that it reflects its essential aspects and provides a more complete cognition. There are different types of models, in this work mathematical models are considered, in which the modelling of objects and processes is carried out using a mathematical description of the object or process under study.

In this work, the objects of study are technological units of oil refining production, which are designed for the systematic production of oil products of a certain quality and in a given quantity. To implement the research results, a specific refinery was selected – a catalytic reforming unit of the LG-35-11/300-95 unit of the Atyrau Refinery.

Based on the research results and the developed mathematical models of the research object, the problems of adopting the optimal operating mode of the reforming unit to economic, environmental and other criteria are solved. Methods of mathematical modelling and decision-making, taking into account the fuzziness of a part of the initial information, are selected as methods for solving the problem posed, which make it possible to effectively manage technological objects and oil refining processes in production conditions. In the course of setting and solving the problem of the monograph, new formulations of the research problem will be formalized, as well as new methods and algorithms for modelling and decision-making in a fuzzy environment will be developed.

Research on models and step-by-step modelling must be practically carried out in order to reduce the time for the creation and industrial development of new processes, various types of equipment and control their work, to optimize production processes. Mathematical methods at various stages of research can be used to solve such problems as the choice of a solution to determine the type of process for oil refining, the choice of the type of technological units and devices, their optimal placement, the optimal solution of the production problem with the selection of optimal operating conditions for each unit of the unit and the entire complex generally.

Recently, the development of oil refining production is carried out mainly through the deepening of refining, separation, purification and other processes, which leads to the complication of units and technology. This complexity appears in the variety of parameters that characterize the course of processes, in a large number of internal connections between parameters and their mutual influence. To conduct the technological process in the desired mode in a complex of technological units, it is necessary to establish a law of interconnection between the input and output parameters of individual units, which can't be done without special means and mathematical apparatus. An effective solution to this problem and control of complex industrial units is possible with the help of computer systems based on mathematical models and algorithms for making an optimal decision, created taking into account the nature and structure of an industrial unit or a complex of units, the type of processes occurring in them, types of modes.

A mathematical model is a system of mathematical descriptions reflecting the features of the processes occurring in the object of modelling (technological unit), which, using a certain algorithm, makes it possible to predict the behavior of the object when the input and control parameters change. Formally, a mathematical description is a set of dependencies connecting various parameters of an object or a process into a single system of relationships [64–66]. Among these ratios there may be expressions that reflect general physical laws (for example, the laws of conservation of mass and energy), equations that describe «elementary» processes (for example, interactions, chemical-physical transformations). In addition, the mathematical description also includes various empirical and semi-empirical relationships between different parameters of the object, the theoretical form of which is unknown or too complex.

Let's consider the main functions of mathematical models used in solving problems of analysis and control of complex technological objects. Modelling can be used to develop a theory of an object, especially if direct investigation of the object or process is impossible, i.e. analysis of models often allows for the development of theory. For example, the current level of knowledge does not allow creating a rigorous theory of vaporization and, on the basis of it, obtaining analytical expressions for determining the heat transfer coefficients during boiling [67, 68]. Modelling makes it possible in some cases to replace calculations with measurements or to simplify the problem.

Mathematical modelling becomes especially expedient when expensive objects are developed or investigated, for example, large technological units for the study of such objects, in determining the rational modes of their operation. The use of mathematical models of complex industrial facilities can bring significant economic benefits. It allows to research the processes occurring in technological units at immeasurably lower costs than field studies on real units, on test benches or on physical models. Finally, a package of mathematical models (models of aggregates combined into a common system) can be used to effectively solve decision-making problems, optimization problems and to develop control actions for the optimal management of the technological process and its intensification.

Thus, the methods of mathematical modelling make it possible to objectively consider and compare many different options according to local criteria and choose the most appropriate one, i.e. are a means of solving direct problems of controlling various objects (modelling), when the influence of the input control parameters of the object on the output is determined. Solutions of such problems in relation to various objects of the oil refining, chemical and other industries are considered in works [68–83].

In addition, on the basis of models that make it possible to determine the dependence of quality criteria on control parameters, it is possible to solve inverse problems. At the same time, the requirements for the output parameter of the object are set, for example, the desired values of the yield and quality of the products obtained, and constrains on the conduct of the process, due to the technological regulations of the unit (intervals of values of operating parameters, control actions, etc.). Then, using special algorithms for making the optimal decision, a set of control parameters is determined that provide effective values for the quality criteria.

Analyzing the obtained optimization results, the choice of alternatives is carried out, i.e. solving inverse problems – decision-making problems [84–88]. Acceptance methods under conditions of indistinctness of the initial information are described, for example, in the following literature [49, 50, 89–91], and the theory of optimization by many criteria is described in [92–95]. Problems and approaches to the solution of the direct and inverse problems discussed above, arising in the management of complex technological objects of oil refining according to economic and environmental criteria, are the purpose of the study of this monograph.

As already noted, the technological units of the oil refining industry consist of several interconnected technological units. Therefore, to conduct the technological process in the optimal mode, it is necessary to have associated mathematical models of the units of the unit, compiled on the basis of a systematic approach. These models should make it possible to predict the influence of the parameters of the units on the processes occurring in them, on intermediate and final products and on the operation of the unit as a whole. Combined information of different types is usually used for the mathematical description of the relationships of the parameters of the studied object of interest to us:

– theoretical ideas about the nature and nature of the process occurring in the object [68, 71, 75, 79];

– initial statistical data characterizing the functioning of the analyzed system [96–99];

– data of expert assessment, including fuzzy information, qualitatively describing the state of the object [100–103].

Depending on the availability of certain types of the listed data, various types of models of plant units can be built. It should be noted that when creating a complex of models for the system modelling of a block, unit, it is necessary to take into account whether the developed types of models of individual units fit well.

According to their purpose, functions performed and accuracy, the following types of models can be conditionally distinguished:

– information models used as advisory systems to study the influence of factors on the output parameters for the development of recommendations for adjusting the operating mode of the unit, etc.;

– optimization models used to find the optimal conditions for the process in the complex of units. Information models can be used as optimization ones, supplemented with a block for assessing the result based on the objective function, taking into account the imposed constrains on the change in input and output variables, as well as an optimization block for finding such a combination of input – control variables at which the output variables reach the desired values;

– process control models used to influence the system in real time in order to compensate for unwanted random disturbances and displacement of the system in the direction of the extreme value of the objective function. Such a model is a component of an automatic control (regulation) system, which includes system state sensors, sensor signal converters, as well as actuators to implement the required impact. These models are subject to increased accuracy requirements.

The main approaches to the building of mathematical models of aggregates are: theoretical, experimental-statistical, an approach based on the use of methods of the theory of fuzzy sets, and a combined approach [72, 104].

Let's consider the main types of mathematical models obtained on the basis of the listed approaches and used in the study and control of technological units of industrial plants.

Deterministic models of technological units and processes are developed on the basis of theoretical ideas about the structure of the described system and the regularities of the functioning of its individual subsystems, i.e. these models are built on the basis of a theoretical approach using equations that describe each of the processes that are essential for a given natural object, for example, there are examples of deterministic models of the most studied physical and chemical processes of oil refining and petrochemistry (fluid and gas movement, heat and mass transfer, kinetics of a chemical reaction, processes in the flow – ideal displacement, displacement, diffusion, etc.) [68, 69].

The modelling of technological units using a theoretical approach is possible mainly for the simplest processes. For more complex aggregates, or when there is a complex of interconnected aggregates, obtaining their deterministic models is almost impossible. This is due to the fact that in these cases there is no or limited theoretical information about the nature of the processes of the simulated object, or the resulting model may turn out to be too cumbersome, complex, its information support (search, determination of model coefficients) is very laborious, so that the development of such the model would be impractical. However, the methodological significance of this approach is important, which makes it possible to assess the state of an object using equations that take into account the general fundamental laws of nature. And these laws, as a rule, reflect and control the processes and phenomena in nature and technology.

Depending on the physical nature of the processes occurring in the system of aggregates and the nature of the problem being solved, the mathematical model may include equations for the balance of mass and energy for all subsystems of the model, equations for the kinetics of chemical reactions, phase transitions, transfer of matter and energy, as well as theoretical and empirical relationships between various parameters of the model and constrains on the conditions of the process. Thus, deterministic models used for the analysis and control of aggregates connect the input parameters of the process $x=\{x_1,x_2,\dots,x_n\}$, called influences, with the output characteristics $y=\{y_1,y_2,\dots,y_m\}$ in the form of a constraint equation [104, 105]:

$$y=f(x), \tag{1.6}$$

where *x, y* – vectors of input and output parameters. Relation (1.6) is a mathematical model of the process that describes the changes occurring in the system, if the similarity of the natural and modelling processes is proved.

Deterministic models are often not suitable for modelling complex technological systems. First, as a rule, it is not possible to describe in the form of equations all the essential aspects of complex processes. Secondly, the performance characteristics of the same systems turn out to be unequal in practice due to the influence of many uncontrollable factors, such as, for example, the difference in operating conditions caused by the wear of various units or parts, fluctuations in the properties of raw materials, etc.

Thus, in industrial conditions, when the states of technological units are simultaneously affected by a large number of parameters, random influences play an important role. To describe such aggregates, consider any real process that is characterized by random fluctuations, for example, caused by physical variability of some factors $x_i+x_i(\tau)$ or external random influences. Due to this, for an equal average value of the input characteristics $x(\tau)$ at times τ_1 and τ_2, the output parameters $y(\tau)$ will be different, therefore, for such stochastic (probabilistic) processes, where random fluctuations $\Delta x_i(\tau)$ cannot be neglected in comparison with $x_i(\tau)$ and random external influences $\xi_i(\tau)$, it is necessary to characterize the system taking into account the statistical law of distribution of instantaneous values $y(\tau)$ relative to the average value $y_{av}(\tau)$ by the equation:

$$y(\tau)=y_{av}(\tau)+\Delta y(\tau)=f(y_{av})+\xi(\Delta x,\xi). \tag{1.7}$$

Models of type (1.7), reflecting the random nature of the parameters and factors of an object, are called *stochastic*. As the values of the parameters *x* and ξ decrease, equation (1.7) continuously approaches in structure to equation (1.6), which describes deterministic systems. That is, statistical models are a broader class of models and include deterministic models as a limiting special case in which the output variables y are uniquely determined by the input variables *x*.

The building and study of a statistical mathematical model includes the development, quality assessment and study of the behavior of the system using some equation or system of equations that describe the simulated unit. In this case, the initial information is obtained on the basis of an experimental – statistical approach, by conducting a special experiment with a real system, for which methods have been created for preparing and conducting such an experiment, processing the results, as well as criteria for assessing the obtained models. This approach is equivalent to the well-known black box research problem; it is possible to talk about a mathematical modelling at the level of statistical information that describes the behavior of an object.

In order to maximize the extraction of information from conducted experiments and reduce their number, experiments are planned, i.e. selection of the number and conditions of experiments, necessary and sufficient to solve the problem with a given accuracy.

To build a statistical model, two types of experiments are used: passive and active [104]. The first type of experiment, due to long-term and passive observation of the progress of the process, makes it possible to collect a wide range of data for subsequent statistical analysis. With an active experiment, it is possible to regulate the conditions of the experiments. Moreover, the most effective is the simultaneous variation of the magnitude of all factors according to a specific plan, while it is possible to identify the interaction of factors and significantly reduce the amount of experiments. Special issues of conducting experiments and processing their results when searching for the optimum are considered in [81].

Thus, it is possible to conclude that the main advantage of statistical models is their simplicity, which allows such models to be widely used in automated control systems for complex technological objects. In a number of cases, statistical models are the most effective means of building a mathematical model of the process, when the system of equations for a complex system turns out to be too cumbersome, and the purpose of modelling is operational forecasting and process control.

However, these models also have significant drawbacks. First of all, statistical models are not meaningful enough. Within the framework of these models, the deep causal relationships inherent in the object are not revealed, and therefore the whole variety of occurrences of processes occurring in the object, the influence of various external factors on these processes are not taken into account. In addition, in statistical models there is no physical substantiation of the relationship between the parameters and the content of various coefficients, and the extrapolation of the results obtained outside the boundaries of the experiment is illegal. As a result, the universality of such models is significantly limited.

One of the difficult problems that arises in mathematical modelling and decision-making on the optimal control of complex production facilities is that the initial information that can actually be collected to solve these problems may turn out to be fuzzy, i.e. is non-numeric. This problem is associated with the fact that most complex objects of oil refining production, as a rule, are difficult to describe quantitatively, and special means for collecting and processing statistical data in industrial conditions are insufficient, do not have the necessary qualities, or are absent. For the development of a mathematical description and modelling of such objects, considered above, the traditional approaches (deterministic, experimental-statistical) are inappropriate, since they require theoretical information or quantitative, statistical data and do not give significant results.

In this regard, in order to increase the efficiency of methods of mathematical modelling and decision-making in the study and control of quantitatively difficult to describe technological objects of oil refining, it is necessary to use and formalize a priori qualitative information about the features of the functioning of these objects, which allows to overcome the problems of uncertainty. Effective formalization of qualitative information, which is knowledge, judgments of expert experts about the object under study, can be carried out on the basis of methods of the theory of fuzzy sets (TFS), the mathematical apparatus of which is described in [58, 59, 61, 106–109].

In practice, an experienced person – an operator is able to control technological objects in a fuzzy environment, based on some model of a qualitative nature, formed in its mind in the process of learning and observing the functioning of the object. Based on the methods of expert assessments and theories of fuzzy sets, it is possible to obtain a formalized model of such an object, without resorting to the help of complex mathematical structures, but based on the ability of a person to express its essence in fuzzy terms of natural language. The simplest model of this type will be the expressions «*if to apply to the input of the system* $\tilde{x}_i$, *then get it at the output* $\tilde{y}_j$», where $\tilde{x}_i \in X$ and $\tilde{y}_j \in Y$ – some terms from the term set $T(X, Y)$. Further, processing the obtained qualitative information using the methods of the theory of fuzzy sets and possibilities, let's obtain a quantitative estimate or model of this object used in the decision-making process. The method for the synthesis of mathematical models in a fuzzy environment developed during this work and the results of its algorithmization are published in [110–112] and are discussed in Section 2.

Thus, the use of the mathematical apparatus of the theory of fuzzy sets and possibilities makes it possible to build simpler and more efficient models and algorithms for solving decision-making problems when controlling technological objects in conditions of uncertainty, when the use of traditional approaches is impractical or impossible.

Along with the effectiveness of the application of the theory of fuzzy sets, it should be noted that there are some problems that arise in its practical application: the non-formalizability of the problems of building the membership function; the complexity of obtaining and systematization of primary quality information; the need for additional verification of the reliability of information; the difficulty of choosing decision rules, represented in the form of conditional sentences for the synthesis of a decision-making algorithm.

In the applied and theoretical aspects of the theory of fuzzy sets, difficulties arise associated with the meaningful interpretation of membership functions and methods of building them. Interpretation of the concept of «membership function» must be given from the real basis of this concept, its sources in real processes. The issues of the interpretation of membership functions for various settings are discussed in [113–115], according to which linguistic and probabilistic interpretation options can be distinguished. Meanwhile, in order to increase the objectivity of the analysis of situations, it is advisable to keep records in one model as much as possible heterogeneous information and, accordingly, the characteristics of its blurring.

In papers [113, 116], methods of building membership functions are considered. The process of building membership functions assumes that expert experts have some objective information about the process under study. The fact that the membership function contains elements of subjectivity reflects the methodology of fuzzy set theory. The fact is that it is precisely the inconsistency of the approach based on the use of quantitative (statistical) data for the study and management of complex systems that has caused the need to create a theory that would make it possible to formalize qualitative information in the common language of people into a rigorous mathematical model. At the same time, due to the complexity of the systems under study, which significantly reduces the reliability of the information received, there is a need to invest in the qualitative knowledge of specialists about the process, even if it roughly reflects the true nature of the functioning.

In practice, when building models of real industrial units, it is necessary to use a *combined approach*, which, if possible, combines the universality of the theoretical, the simplicity of the experimental-statistical approach and the possibility of taking into account additional qualitative information based on the methodology of the theory of fuzzy sets. At the same time, various options for combining these approaches are possible.

For example, to assess the state of an object, equations describing general conservation laws are used, and individual coefficients of the model are determined by an experimental-statistical method.

To assess the results of the operation of production facilities, as a rule, a vector of criteria is used, which may also be fuzzy. On the basis of these criteria, decisions are made on the choice of the optimal operating mode of the technological object [77, 87, 117]. In this case, the problems are reduced to minimizing or maximizing the criteria. It is clear that if the quality criterion is productivity, profit, target product yield and other technical and economic indicators and environmental requirements, then the problem of improving these indicators is solved.

Let's characterize mathematical models of a technological unit by a finite set of parameters, which can be conditionally divided into three groups: internal, external and output.

Internal parameters are understood as parameters characterizing the course of a process, for example, operating parameters of an object. External parameters characterize the influence of the external environment on the optimized object. Output parameters reflect the main properties and characteristics of the optimized system, for example, technical, economic and environmental performance of production.

Not all internal parameters are equal: usually only some of them can vary during the optimization process. Variable internal parameters are called controlled parameters or optimization parameters and form a vector $x=(x_1, x_2, \ldots, x_n)$. In the absence of uncertainty factors, all external and unchangeable internal parameters take on known, predetermined values. As a result, a deterministic model is obtained, which is used for algorithmic optimization of the operating modes of a technological object [118].

Let's consider the basis of the decision-making (DM) process for choosing the optimal operating mode of technological objects of oil refining in conditions of multi-criteria [119–122].

Decision making consists in assessing possible solutions (alternatives) and choosing the best one according to the given criteria. The implementation of any solution option presupposes the onset of certain consequences, the analysis and assessment of which, as a rule, according to several (vector) performance criteria, fully characterizes this solution option. The DM problem arises when there are several options for action (alternatives) to achieve a given or desired result. In this case, it is required to choose the best alternative in a certain sense. Solving DM problems is reduced to identifying and studying the preferences of the decision-maker, as well as building on this basis an adequate model for choosing the best, in a sense, alternative.

The general formulation of the DM problem, understood as the problem of choosing the optimal operating mode of the object from a certain admissible set of alternatives (solution options – the operating modes of the object), can be formulated as follows.

Let X – the set of modes of operation of the object (alternatives), Y – the set of possible DM consequences (outcomes, results). X, Y – generally speaking, arbitrary abstract sets. It is assumed that there is a causal relationship between the choice of some alternative $x_i \in X$ and the onset of the corresponding outcome $y_i \in Y$. In addition, it is assumed that there is a mechanism for assessing the quality of such a choice, which is usually the quality of the outcome.

Let's proceed to the analysis of the formulated DM problem. The first important point is to determine how alternatives are associated with outcomes. As it is possible to see from the examples, this relationship can be deterministic (or, as is often said, deterministic). In this case, there is a unique mapping:

$$x \xrightarrow{\gamma} Y, \tag{1.8}$$

where γ – operator mapping.

In this case, the function $y = \varphi(x)$, $x \in X$, $y \in Y$ is implemented.

The same connection can have a probabilistic nature, when the choice of x determines a certain density of the probability distribution on the set Y. In this case, the choice x_i no longer guarantees the onset of a certain outcome y_j, and the DM problem itself is called the DM problem under risk conditions.

DM problem can be illustrated using **Fig. 1.2**.

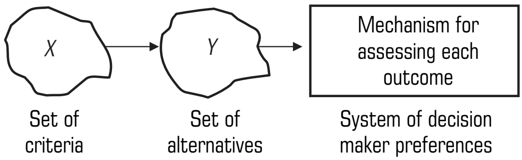


Fig. 1.2 DM problem illustration

A characteristic feature of the decision-making process in the management of production facilities, in which a person plays a special role, is not only the need to use computer systems, but also in attracting the judgments of managers, specialists – decision makers [123, 124]. The information obtained on the basis of the decision maker's judgments makes it possible to reveal its preferences regarding the values of the criterion, when compiling the values of various criteria and is very important for choosing a solution.The purpose of making decisions is to transfer the state of the object at the current time to some desired area of the state. At the same time, conditions must be created to ensure this transfer. For production facilities, they usually strive to achieve an extreme value, as a rule, of several criteria, at which a purposeful change in the state of the object to the desired area is performed, depending on the specific situation prevailing in production at the current time.

Thus, decision making is determined by the difference between the actual and the desired state of the object, the degree of the decision maker's awareness of the state and purposes of the object's functioning. When concretizing the decision-making problem, the means, resources and parameters are determined that must be changed to achieve the desired area, i.e. formulate the DM problem.

In general, the DM problem can be written as:

$$<\text{DM problem}> = \{\text{give } V,\ V_S,\ V_P, \text{ it is required to provide } W\}, \quad (1.9)$$

where V – specified conditions; V_S – set of possible states of the object; V_P – set of possible operators that ensure the transition of an object from one state to another; W – desired state of the object.

In this case, the solution to the DM problem consists in choosing a sequence of operators to transfer the object from the state at the current moment to the desired state.

Depending on the DM problem and the complexity of objects, two main methods can be distinguished: holistic choice, when the decision maker operates directly with alternatives, and criterion-expert choice, when the decision maker forms a set of criteria and constrains, assigns a selection rule, and the criteria are assessed as a result modelling or interaction with the system, while some of the alternatives are assessed by experts. The practical use of the first method is very limited for complex objects, such as industrial ones, since the decision maker operatively operates with a limited amount of information (7±2 structural units of information – alternatives).

Multidimensionality, qualitative differences in criteria, possible uncertainty of the model of production systems in combination with fuzziness serve as serious obstacles in obtaining an assessment of the quality of an object and necessitates considering more general approaches to the concept of optimality, i.e. development and development of new methods in decision theory for multi-criteria fuzzy problems. The intensive development of this theory was facilitated by the wide and effective use of computer technology, which makes it possible to analyze and process large amounts of data.

Many DM problems have the following characteristic feature: a model describing a set of feasible solutions is objective, but the quality of a solution is assessed by many criteria. In order to choose the best solution, a compromise is required between the assessments according to different criteria. In the conditions of the problem, there is no information that allows to find such a compromise. Consequently, it cannot be determined on the basis of objective calculations [125].

Let's consider the problem of multi-criteria when making a decision. Multi-criteria DM problems arise when it is required to choose the best solution at once according to several conflicting local criteria. So, in production management problems, it is usually necessary to maximize the output of target products with the required quality indicators, with limited costs, costs and losses.

Since there is usually no best solution for all criteria at the same time, a reasonable compromise is necessary. So, as soon as a person (decision maker) can know which indicators are more important, then the solution of multicriteria problems should be based on information about the preferences of the decision maker.

With the appearance of many criteria, the problems of choosing the best solution acquire the following features:

– the problem has a unique, new character – there are no statistical data to justify the relationship between the various criteria;

– at the time of making a decision, there is fundamentally no information that allows an objective assessment of the possible consequences of choosing one or another solution option. But since the decision, one way or another, must be made, the lack of information must be filled. This can only be done by people based on their experience and intuition.

In multicriteria problems, part of the information necessary for a complete and unambiguous determination of the requirements for a solution is fundamentally absent. The researcher can often determine the main variables, establish connections between them, that is, build a model that adequately reflects the situation. But the dependencies between the criteria cannot be determined at all on the basis of objective information at the disposal of the researcher. Such problems are weakly structured, since the lack of objective information here is fundamentally unavoidable at the time of making a decision.

Problems of multi-criteria choice with fuzzy initial information have become the subject of research by scientists relatively recently. The most intensive developments in this direction began at the Riga Polytechnic Institute in the works of A. Borisov and others [126, 127]. The main «bottleneck» on the way of widespread use of the developed approaches and algorithms for solving multi-criteria DM problems in a fuzzy environment is the convolution (mainly linear) of the vector efficiency criterion and vector fuzzy relations of preferences. Other disadvantages of these approaches, which impede their application in solving production management problems, include:

– use of the concept of «fuzziness» mainly only when it comes to relations of preference (in the sense of the degree of superiority of one option over another);

– attempts to calculate a strict fuzzy preference ratio without taking into account the opinions of the decision maker;

– shortcomings in the study of issues of human-machine interaction in the formalization and solution of DM problems, a low level of «intelligence» of the user interface and software and algorithmic support for human-machine systems for solving these problems.

There are problems in which only a list of basic parameters is known, but quantitative relationships between them cannot be established (there is no necessary information). Sometimes it is only clear that changing the parameter within certain limits affects the solution. In such cases, the structure, understood as a set of relationships between parameters, is not defined, and the problem is called unstructured. Weakly structured and unstructured problems are explored in the framework of a scientific field called multi-criteria decision making.

Depending on the well-knownness of the initial set of alternatives – Ω and the optimality principle – $\underset{\Omega}{\text{opt}}$, the DM problem is classified:

– general problem of decision making – Ω and unknown;

– choice problem – Ω is known, unknown;

– general optimization problem – Ω and $\underset{\Omega}{\text{opt}}$, – are known.

The DM problems, depending on the relationship between situations, alternatives and outcomes of the decisions made, are divided into: DM problems in conditions of certainty, risk and in a fuzzy environment.

DM problems under certainty conditions (deterministic DM problems) are characterized by an unambiguous deterministic connection between the alternatives X_i and the outcome S. It is assumed that the initial set of alternatives $\Omega = \{X_i\}$ and unambiguous estimates of the outcome S in the form of criteria $f_1(x_i)$, $f_2(x_i)$, ..., $f_m(x_i)$, $f(x_i)$ will be called a vector criterion.

In these cases, the DM problem is formalized as a selection problem (vector optimization):

$$\max_{x\in\Omega} f_i\left(x\right),\ i=\overline{1,m},\ x=\left(x_1,x_2,\ldots,x_n\right). \tag{1.10}$$

In this form, problem (1.10) is not correct and only reflects the desire to make the value of local criteria larger. In these problems, it is necessary to clarify the concept of optimality. This concept should be, on the one hand, close to the idea of optimality of the decision maker, and on the other hand, formalizable enough to be able to work with it algorithmically, and not intuitively. The optimality principle defines the concept of the best alternatives.

Different methods for solving such multi-criteria DM problems differ in the way they aggregate estimates for individual criteria into a common one. The main methods of solution include:

– *direct methods*, in which the dependence of the overall assessment on assessments by particular criteria is selected in advance in one way or another, for example, with the help of a decision maker;

– *compensation methods* – based on the idea of compensating the assessment of one alternative by the estimates of another, in order to find which alternatives are better. In theory, this is the simplest method in which the decision maker writes out the advantages and disadvantages of each of the alternatives and, crossing out the pairwise equivalent advantages (disadvantages), studies the remaining assessments according to the criteria;

– *methods of comparability thresholds*, here the rule for comparing two alternatives is set, in which one alternative is considered better than the other. In accordance with the given rules, alternatives are divided in pairs into comparable (best, equivalent) and incomparable. When the condition changes, the number of comparable alternatives changes. This changes the composition of the so-called core (for example, the Pareto set), which includes alternatives that turned out to be not the worst in all comparisons, i.e. the best solutions are highlighted;

– *axiomatic methods*, in which a number of axioms are determined, which must satisfy the dependence of the general utility on estimates by local criteria. These axioms (properties) are verified by obtaining information from the decision maker, according to which a conclusion is made about one form or another of dependence;

– *man-machine (dialogue) methods* are used when the problem model is known in part. The decision maker interact with the computer, defining the relationships between local criteria, it first determines the initial requirements for the criteria relationships, enters into the computer, receives the real values of the criteria, changes its requirements, re-enters the computer, etc. In the course of such iterations, the decision maker clarifies the characteristic features of the problem, identifies and clarifies its preferences and, as a result, provides additional information, thanks to which the computer develops more and more perfect solutions. Such a dialogue between the decision maker – the computer, in the presence of a user-friendly interface, contributes to the development of a reasonable compromise in the decision maker's requirements for the values achieved according to different criteria.

Stochastic decision-making problems (DM problems at risk) arise in those cases when each decision $x_i \in \Omega$ is associated with a set of outcomes from m possible outcomes $S_1, \ldots, S_n$ with known probabilities $P\left(S_j \middle| x_i\right)$, $i = \overline{1,n}$, $j = \overline{1,m}$, i.e. in these problems, there is no unambiguous connection between alternatives and outcome. When $P\left(S_j \middle| x_i\right) = 1$, the DM problems at risk and the deterministic DM problems coincide.

To solve DM problems at risk, methods of the theory of stochastic programming, games, queuing and other probabilistic methods are widely used. Let be determined $l_{ij} = P\left(S_j \middle| x_i\right)$ – the utility function of the outcome S_j when making decisions and – conditional probabilities characterizing the transition of the object to the state S_j when using the strategy x_i, then the utility of each decision is represented in the form:

$$u\left(x_i\right) = \sum_{i=1}^{m} f\left(S_j, x_i\right) p\left(S_j \middle| x_i\right), \; i = \overline{1,m}.$$

In this case, the choice of a solution is carried out according to the following rule, which ensures the achievement of the maximum value of the expected utility:

$$x^* = \arg\max_{x \in \Omega} \left\{ u\left(x_i\right) \right\}.$$

DM problems in a fuzzy environment. Let's assume that in decision-making situations, when at least one of the elements of the problem (alternatives, criteria, preferences and constraints) is described indistinctly, DM problems take place in a fuzzy environment (with fuzzy initial information). In this monograph, it is precisely such DM problems that are mainly investigated.

A promising direction in the development of DM methods in a fuzzy environment is a linguistic approach based on the theory of fuzzy sets. To date, concrete practical results have been obtained in this direction. However, some situations that have developed in production under conditions of uncertainty require new approaches to the formalization of DM problems and the development of methods for their solution.

The methods and algorithms developed in this work for solving DM problems in a fuzzy environment, as well as examples of their implementation, are considered in Section 3.

Thus, in practice, when modelling and making decisions on the management of production facilities according to many criteria (of an economic and environmental nature), it is necessary to develop and apply methods that are workable in conditions of multi-criteria and uncertainty caused by the deficit, randomness and indistinctness of the initial information.

1.6 STATEMENT OF RESEARCH OBJECTIVES, PROBLEMS AND APPROACHES TO THEIR SOLUTION

The tasks of mathematical modelling in order to make a decision on the choice of the optimal mode of operation of technological objects of modern oil refining production are usually multi-criteria. The main criteria in decision-making and management include increasing productivity, ensuring the desired qualities of the products produced, reducing their cost, saving materials and resources, ensuring stability and improving the ecological state of production, protecting the environment and the health of personnel, etc., and often they are contradictory.

Depending on economic (quantity and quality of products, production costs, etc.), production (product production plans, unit repair schedule, etc.), technological (process parameters) and environmental (environmental issues) and other factors, these criteria are different. importance, and with a change in these factors, the mutual importance of the criteria also changes. In this monograph, the main criteria for optimizing oil refining facilities are groups of economic, technological and environmental indicators of production.

Thus, the problems of making the optimal decision in the management of technological objects of oil refining, which are characterized by multi-criteria, are reduced to solving vector optimization problems, which allow to find the area of effective solutions. And the final choice and decision-making can be carried out by the decision maker (the person making the decision – in our case the head of the shop or unit, the technologist and senior operators) based on their preferences, situations in production and the market, as well as information obtained in dialogue with the computer support system decision making.

To formalize and solve problems of optimization and control of multicriteria objects, which is a complex of technological units for oil refining, it is necessary [104, 128, 129]:

1. Identify the operating conditions of the units and their connection with other objects.

2. Select the local criteria for the object, i.e. indicators of operating modes of units and systems that need to be optimized.

3. Determine the control parameters, changing which it is possible to achieve the optimal values of the criteria.

4. Formulate the problem of making decisions on the choice of optimal operating modes of the technological object.

5. Develop a system of mathematical models of technological units that describe the relationship of control actions with the values of local quality criteria.

5.1 Collection of available data (theoretical, experimental-statistical, expert and fuzzy).

5.2 Based on the collected data, identify the types of models that can be built for each technological unit.

5.3 Analysis and selection of the type of aggregate models (based on comparison and selection criteria).

5.4 Building of individual models of units and their integration into a system.

6. Correction of the formulations of the DM and management problems.

7. Selection, modification or development of algorithms for solving DM problems for the selection of the optimal operating mode of technological objects.

8. Development of software for decision support system and technological complex management.

Subclauses 5.1–5.4 of the stage – development of mathematical models of aggregates – reflect the essence of the methodology proposed in [128] for building mathematical models of a complex of interconnected aggregates. In this work, on the basis of this technique, a system of mathematical models of technological units of the reforming unit of the LG unit of the Atyrau refinery will be developed.

Let's consider the formal formulation of decision-making tasks for the choice of the optimal operating mode of a complex of technological units. Let there be related mathematical models of units of a technological unit, i.e. operator that adjusts the vectors of input, mode parameters, affects the process and the vector of output parameters $y=\left(y_1,\ \ldots, y_m\right)$ used to control it $x=\left(x_1,\ \ldots, x_n\right)$:

$$y_j=f_j\left(x\right),\ j=\overline{1,m}. \tag{1.11}$$

Aggregate models (1.11), depending on the purpose of modelling and on the available information, can be built in various ways, which are described above, and the requirements that determine the ease of combining individual models into a system must be taken into account.

Local optimality criteria or partial objective functions:

$$f_i\left(x,y\right)\geq 0,\ i=\overline{1,m}, \tag{1.12}$$

are combined into a vector function (if the control criterion is unique, then into a scalar function, $i=1$) of vector arguments x, y, which expresses the decision maker's interest in a particular operation mode of the object, depending on the current production situation. For example, when controlling a technological unit that produces several products, the task may be set to increase the yield of some products, keeping the yield of the rest at a certain level, or to improve the quality of the target product by reducing other indicators.

For given x, y functions f_i take on certain values. One of the tasks is to select such vectors x, y that select the Pareto-set region, where improvement of any of the criteria $f_i\in f,\ j\in K$ is possible only due to the deterioration of others – $f_1=f,\ 1\in K,\ 1\neq q$, K – a set of indices.

Since, according to (1.11), the vector *y* is itself determined by specifying the vector *x*, it can be assumed that the objective functions that estimate the volumes of products and their quality depend only on the vector of input, operating parameters *x*. Then the problem of making a decision on the choice of the optimal operating mode of the technological complex is posed in the form of a multicriteria problem of optimizing the operating modes of control objects: it is necessary to find a control vector $x^* = \left(x_1^*,\ldots,x_n^*\right)$ that provides the best approximation to the desired values of local quality criteria $f_i^*\left(x^*\right)$, while fulfilling the constraints imposed on controls and criteria.

Approaches to the choice of a solution in multicriteria problems based on the decision maker's preferences are considered in decision theory [70, 81, 89, 130–134].

The main difficulty in solving the problems of multipurpose control is associated with the setting of the principle of optimality. In vector optimization problems, there are many different principles (principles of equality, absolute and relative concessions, lexicographic principle, principle of highlighting the main criterion), each of which leads to different solutions. This imposes serious requirements on the choice of the principle of optimality, which gives an answer to the main question – in what sense is the chosen solution optimal, i.e. better than all other solutions.

Let's consider the main problems associated with the solution of multicriteria DM problems that arise when choosing the optimal operating mode of technological units.

1. The problem of determining the area of compromise. In vector optimization problems, there is a contradiction between some of the criteria. Due to this, the domain Ω_A of feasible solutions splits into two non-intersecting parts: the domain of agreement Ω_A^A, where there are no contradictions between the criteria, and the domain of compromises Ω_A^C, which coincides with the Pareto set, i.e. there are conflicting criteria, and improving the quality of a solution for some criteria worsens the quality of a solution for others. It is clear that the rational mode of operation of the unit (optimal solution) can only belong to the area of compromise, i.e. $\omega \in \Omega_A^C$, because in the area of agreement, the decision can be improved on several criteria without worsening on the rest. Consequently, the search for rational modes of the result of this stage is the narrowing of the range of possible solutions to the Pareto set.

2. The problem of choosing a compromise scheme that makes it possible to build a convolution of control criteria. The search for rational operating modes of the unit in the area of compromise can be carried out only on the basis of a certain compromise scheme. Since the number of possible compromise schemes is large, the choice of a specific scheme is a difficult problem and is usually decided based on the preferences of the decision maker. The choice of the compromise scheme corresponds to the disclosure of the meaning of the optimization operator opt in the expression:

$$\text{opt}\, f\left(A\right) = \max \varphi\left(f\left(A\right)\right),\ A \in \Omega_A,\ A \in \Omega_A^C,\ A \in \Omega_A^K, \tag{1.13}$$

where the symbols A and f denote the value of the alternative (*A*) and the corresponding value of the criteria vector *f*, $\varphi(f)$ is some scalar function of the criteria vector *f*, (the function of convolution of local criteria).

Thus, the choice of one or another optimality principle reduces the vector problem to an equivalent scalar optimization problem.

3. Normalization of criteria. This problem occurs if the local criteria have different units of measurement. It is necessary to normalize the criteria, i.e. bring them to the same units or dimensionless scale. To date, several different normalization schemes are known [135].

4. The problem of considering the priority of criteria. Criteria priorities are taken into account in most folding methods by specifying a vector of criterion importance coefficients (weights) $\lambda = (\lambda_1, \lambda_2, ..., \lambda_k)$, where λ_i – the criterion weight. As a result of normalization and consideration of priorities, instead of the original vector estimate $f(A)$ of alternative A, a new vector estimate is formed:

$$\varphi(f(A)) = \lambda_1 f_1(A), \lambda_2 f_2(x), ..., \lambda_m f_m(A), \tag{1.14}$$

where $f_i(A)$, $i = \overline{1,m}$ – normalized values of the criteria.

When solving these and other problems that arise when solving multi-criteria DM problems and developing control systems for industrial facilities, it is necessary to use various kinds of heuristic procedures, in which a significant role belongs to experts, the preferences of the decision maker.

The subject of research in this research work is the development of methods for modelling and making optimal decisions using the latest advances in mathematical methods and computer technology.

In this paper, the author proposes an approach that allows one to formalize and solve the original fuzzy problem without transformation, while maintaining the fuzzy and multi-criteria nature of the problem based on the modification of various compromise decision-making schemes.

Let's consider general approaches (idea) to formalization and solution of multi-criteria DM problems for choosing the optimal operating mode of oil and gas production facilities according to environmental and economic criteria in the presence of the above-mentioned problems of the fuzziness of the initial information.

Let $f_1(x), ..., f_m(x)$ be the local criteria of an economic and environmental nature, according to which the optimal operating mode of the investigated production facility – the technological complex of oil refining – estimated and selected. Each of these criteria depends on the vector of n parameters (input actions) $x = (x_1, ..., x_n)$ and can differ in their coefficients of relative importance (weights) $\gamma_1, ..., \gamma_m$.

Each local criterion $f_i(x)$ is associated with the value of input actions, this dependence is described by the model of the investigated object.

In general, the DM problem of oil refining production facilities, which is characterized by multi-criteria and fuzzy initial information, can be formalized in the form of multi-criteria fuzzy mathematical programming (FMP) problems.

Let $\mu_0(x) = (\mu_0^1(x), ..., \mu_0^m(x))$ be the normalized vector of criteria: $\mu_0(x) = \varphi(f_i(x))$ assessing the operating mode of the technological complex of oil refining, taking into account economic indicators and environmental protection measures. Let's suppose that the membership functions of the fulfillment of constraints $\mu_q(x)$ for each constraint $f_q(x) > b_q$, $q = \overline{1,L}$ are built as a result of a dialogue with the decision maker, experts. Then the general multicriteria DM problem in a fuzzy environment can be written as follows:

$$\max_{x \in X} \mu_0^i(x), \; i = \overline{1,m}, \tag{1.15}$$

$$X = \left\{x: \arg \max_{x \in \Omega}, \, q = \overline{1,L}\right\}. \tag{1.16}$$

On the basis of various compromise decision-making schemes, the principles of optimality, it is possible to obtain a family of statements of multi-criteria DM problems (in the form of FMP problems) and propose specific algorithms for their solution. Specific formulations of multicriteria DM problems in a fuzzy environment, as well as the used, modified and developed algorithms for their solution will be given in the subsequent sections of this monograph.

1.7 CONCLUSIONS OF SECTION 1

1. The current state of the problems of mathematical modelling of technological objects of oil refining production is analyzed, the main characteristics and issues of increasing the efficiency of their functioning according to economic and environmental criteria are considered, as well as the issues of solving the DM problems for choosing the optimal operating modes of the complex of the objects under study. The results of the study of various approaches to the building of models of technological objects of oil refining and optimization of their operation have shown that the use of traditional methods of modelling and decision-making in industrial conditions is often ineffective due to the lack, inaccessibility or insufficiency of reliable information about the parameters and state variables of the objects. Under these conditions, one of the promising means of obtaining and processing the initial fuzzy information (knowledge, experience of experts) for the purpose of efficient modelling and selection of optimal modes of technological objects is the methods of expert assessments and the theory of fuzzy sets.

2. The approaches to the mathematical description of production systems under conditions of uncertainty have been investigated and described. Explanations are given to the basic concepts and elements of the theory of fuzzy sets are considered, which are used in this work as a mathematical formalization apparatus and the use of fuzzy information in the development of models and in solving decision-making problems.

3. One of the insufficiently studied and completely unresolved issues in the scientific literature is the problem of developing a system of mathematical models of a complex of technological units, taking into account the fuzziness of the initial information. In this case, depending on what is available, incl. and fuzzy information, a system of models of objects of various types (deterministic,

statistical, fuzzy, combined) can be built, and their integration into a system of models depends on the purpose of modelling.

4. The tasks of making decisions on the choice of optimal operating modes of technological objects are usually characterized by multicriteria and fuzziness. Such problems are effectively solved in an interactive mode with a computer system for modelling and decision support, with the help of which multicriteria optimization of the operation modes of the object is carried out on the basis of mathematical models of aggregates and taking into account the preferences of the decision maker. The most effective management of a complex of aggregates is ensured by the creation of a decision-making system, in which, depending on the production situation and the preferences of the decision maker, the search and selection of a solution is carried out according to different algorithms. Moreover, these systems should take into account possible changes in the mutual importance of local quality criteria.

5. The research task is formalized and the general statement of the DM problem is given for the choice of optimal operating modes of technological objects of oil refining in production conditions, i.e. when they are characterized by multicriteria of economic and environmental nature and indistinctness (in whole or in part) of the initial information, the arising problems and approaches to their solution are considered.

2 RESEARCH OF THE PRINCIPLES OF DEVELOPMENT OF MATHEMATICAL MODELS OF CHEMICAL AND TECHNOLOGICAL SYSTEMS AND BUILDING MODELS OF A CATALYTIC REFORMING UNIT

ABSTRACT

This section is devoted to the study of the operating modes of the reforming unit of the catalytic reforming unit and the building of mathematical models of the main units of the unit under study. An approach to creating a package of models for systemic modelling of technological systems is proposed on the example of a reforming unit, criteria for building a complex of models are determined and a table is built on the basis of which an effective type of model is selected for each unit of a technological complex of a reforming unit.

A methodology for the development of models of interconnected technological units of chemical-technological systems is proposed. The novelty, which consists in the application of a systematic approach, the use of fuzzy information and other available data, which allows to solve the problems of uncertainty. The methodology makes it possible to build the most efficient type of models for individual units of the technological system, create a package of models and carry out system modelling of the unit in order to determine the optimal modes of its operation.

Mathematical models of the main units of the hydrotreating unit of the catalytic reforming unit LG-35-11/300-95 of the hydrotreater are being developed: a reforming reactor; stripping columns, absorbers and hydrotreating furnaces. Since these objects of modelling the reforming unit of the Atyrau refinery operate under conditions of shortage and indistinctness of initial information, their mathematical models are developed on the basis of a systematic approach, using available information of a different nature (experimental statistical data, fuzzy information from experts) with the use of appropriate methods for building mathematical models.

An algorithm for the synthesis of a linguistic model of a technological complex of oil refining in conditions of fuzzy input and output parameters is proposed. In order to collect the necessary information in conditions of uncertainty, expert assessments were carried out to develop a mathematical description of the technological complex of the reforming unit, a method for conducting expert procedures in a fuzzy environment was developed. The modelling of the operation of the units of the reforming unit of the LG unit is carried out, the modelling results are compared with the results of known methods and experimental - production data, the advantages of the proposed modelling methods are shown, which allow effectively simulating a technological complex in a fuzzy environment.

KEYWORDS

Reforming block, fuzzy model, linguistic model, expert assessment method, expert judgment in a fuzzy environment.

2.1 DESCRIPTION OF THE RESEARCH OBJECT – CATALYTIC REFORMING UNIT OF THE LG-35-11/300-95 UNIT OF THE ATYRAU REFINERY

In this section, let's consider the features of the object of modelling and optimization – a complex of interconnected technological units of the catalytic reforming unit of the LG unit (Leningrad – Germany), the Atyrau refinery, and on the basis of the study, let's develop mathematical models of the object of study.

Catalytic reforming of gasolines is the most important process in modern oil refining and petrochemistry.

It serves for the simultaneous production of a high-octane base component of motor gasolines, aromatic hydrocarbons – raw material for petrochemical synthesis – and hydrogen-containing gas (HCG) – technical hydrogen used in the hydrogenation processes of oil refining. LGs are available in almost all domestic and foreign oil refineries.

Since 1971, an LG-35-11/300-95 unit has been operating at the Atyrau Refinery, its capacity for raw materials is 300 thousand tons/year. It is operated according to the gasoline version with the receipt of a high-octane component with an octane rating of up to 95 points according to the research method.

The target product is a high-octane component of commercial gasolines and liquefied domestic gas.

Used catalysts: hydrotreating unit – catalyst UOP – S-12T; reforming unit – catalyst UOP – R-56. Hydrotreating pressure – 27–28 atm; on reforming – 22 atm; temperature – 470–500 °C [136].

The catalytic reforming unit consists of four units:

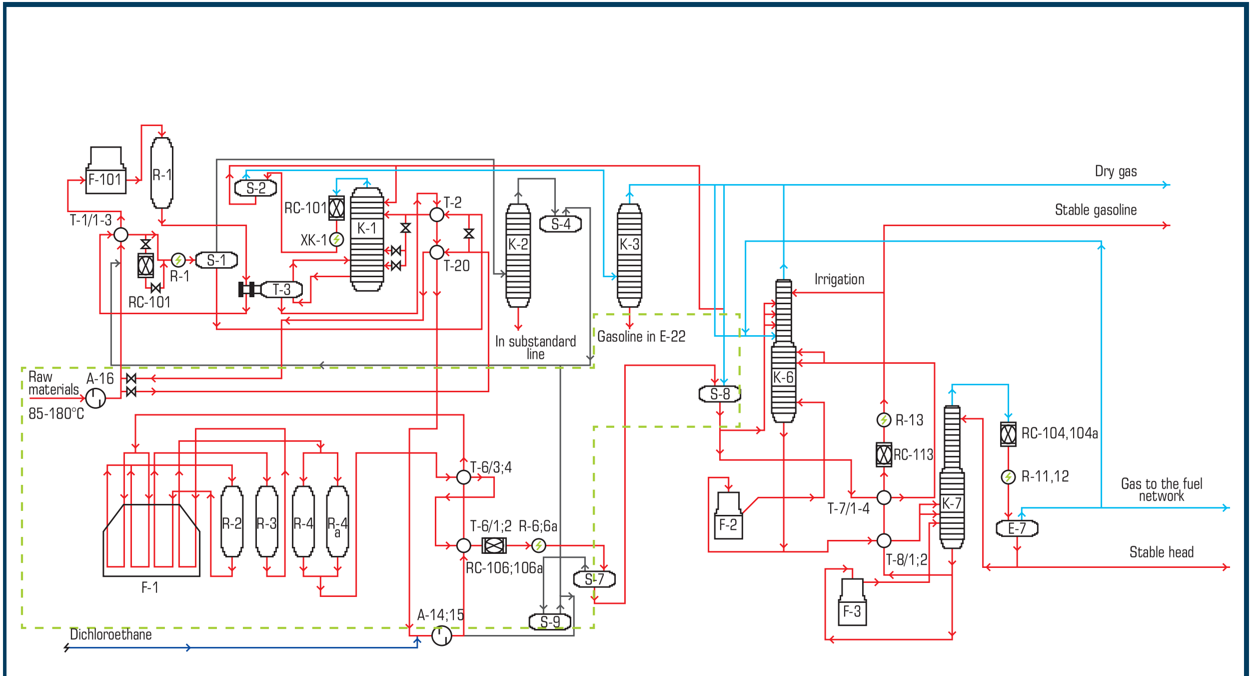
1. Unit of preliminary hydrotreating of raw material – straight-run gasoline.
2. Unit of catalytic reforming (platforming of hydrotreated gasoline).
3. Unit of deethanization and stabilization of catalyzate (platform).
4. Unit of purification of circulating and hydrocarbon-containing gases MEA (monoethanolamine) and regeneration of MEA (under conservation).

Let's consider the description of the technological scheme and the technological process of the unit for the investigated unit – the catalytic reforming unit, the technological scheme of which is shown in **Fig. 2.1**.

Catalytic reforming unit. The purpose of reforming is to convert naphthenes and paraffins into aromatic hydrocarbons, which are then used as commercial gasoline in the composition of the process product – platformate (due to its high octane numbers).

The catalytic reforming process is based on the reactions of dehydrogenation and dehydroisomerization of naphthenic hydrocarbons, isomerization of alkane hydrocarbons on a platinum catalyst under high hydrogen pressure.

As a result of these reactions in the raw material (in gasoline fractions), the amount of isostructural aromatic hydrocarbons, which have high octane characteristics, increases.



Designation of technological lines: 1. Red – Gasoline; 2. Gray – HCG; 3. Green – technical water; 4. Light blue – Process gas; 5. Blue – Dichloroethane

Fig. 2.1 Process flow diagram of a catalytic reforming unit, the reforming unit is highlighted with a green dotted line

The hydrogenated product, freed from hydrogen sulfide and water, from the T-3 heater enters the T-2 heat exchanger, then to the T-20 and to the intake of centrifugal pumps. From here, the reforming raw material under a pressure of up to 50 atm is mixed with a circulating gas. The mixture of hydrogenated product and circulating gas is heated in heat exchangers T-6 to a temperature of no more than 460 °C due to the heat of the mixture leaving the reactors R-2, 3, 4, 4a and then enters the corresponding chamber of the F-1 furnace for heating.

In order to increase the activity of the catalyst before entering the reactors R-2, R-3, R-4, 4a, dichloroethane is injected into the mixture. For reforming, the mixture passes through reactors R-2, 3, 4, 4a with appropriate intermediate heating in a multi-chamber furnace. The aromatization reaction of gasoline proceeds with a negative thermal effect, as a result of which the temperature in the reactors decreases. To restore the temperature in the reaction zone, multistage heating is provided in the 2nd and 3rd stages of the P-1 multi-chamber furnace to a temperature of 490–530 °C. The conversion rate of raw materials by reaction stages is: in the first stage – 53–60 %; in the second stage – 28–30 %; in the III stage – 10–14 %.

The gas-product mixture from reactors R-4 and R-4a with a temperature of 490–530 °C is directed in two parallel streams into the tube space of heat exchangers T-6 / 3-4, where it is cooled to a temperature of 250–300 °C. Then the mixture is sent to the high-pressure separator C-7, where the gas-liquid mixture is separated into HCG into liquid catalyzate. HCG from the top of the C-7 high-pressure separator is sent to the C-9 reformer circulation gas separator, from where it is returned to the reforming system.

Unstable catalyzate from the bottom of the high-pressure separator S-7 is sent for further separation to the low-pressure separator S-8, where, by reducing the pressure to 19 atm, hydrocarbon gas is released from the catalyzate. This gas, together with the gases of the K-3 absorber, is sent to the K-6 fractionating absorber. The rest of the catalyzate is sent to the heat exchanger T-7, where it is heated by the heat of the stable catalyzate to a temperature of 156 °C and enters the lower part of the fractionating absorbent K-6.

2.2 PRINCIPLES OF MODEL SELECTION BASED ON SYSTEM ANALYSIS AND EXPERT ASSESSMENT OF THEIR TYPES

As a result of the analysis of various methods for the development of mathematical models of complex objects, it was revealed that in research works, the issues of systemic modelling of a technological complex, consisting of interconnected technological units in conditions of a lack of quantitative information, were revealed, such as technological units of the catalytic reforming unit of an LG unit. In conditions of uncertainty associated with a deficit of initial information, it is proposed to apply probabilistic modelling methods or methods of modelling modelling [97, 99].

However, the application of these methods is impossible if the uncertainty is associated with the fuzziness of the initial information, which often occurs in real production conditions. Under these conditions, statistical information is absent or insufficient, and the axioms of probability theory (statistical stability of the object of study, repeatability of experiments under the same conditions) are not fulfilled. Sometimes the available information is only fuzzy (high-quality, meaningful) information, which is knowledge (experience, intuition, judgments) of a person – decision maker, production personnel, specialist-expert.

With the competence of these sources of information and with the correct organization of their interrogation, collection and processing of such fuzzy information on its basis, it is possible to build models that take into account all the complex relationships of various parameters and variables of a production facility. The resulting models can be more meaningful than the models developed by traditional methods, and most importantly, adequately describe real production facilities and tasks.

Let's consider the proposed method for creating a package of mathematical models of interconnected units of a technological complex on the example of developing a package of models for technological units of a catalytic reforming unit of a technological system – LG.

A catalytic reforming unit is a complex object consisting of interconnected blocks and their system of aggregates, which are simultaneously influenced by a large number of different parameters. The main units of LG include reactors (hydrotreaters R-1; reforming R-2, 3, 4 and 4a), columns (stripping K-1, absorbers K-2, 3, 6; stabilization K-7), furnaces (F-101, P-1; P-2, 3), separators, heat exchangers, etc. (**Fig. 2.1**).

The units and units of the unit are interconnected and changes in the operating parameters of one of them lead to changes in the parameters of the others, which affect the processes. In this regard, in order to optimize and control the reforming process in the optimal mode, it is necessary to have a package of related mathematical models of blocks and main units of the plant, compiled on the basis of a systematic approach, taking into account the influence of technological parameters on each unit, on intermediate and final products and on operation of unit as a whole [103].

Models of each object in the system can be built using various approaches and methods discussed in Section 1, i.e. it is possible to get a set of models for each LG unit, for example, statistical, fuzzy or combined.

To combine such models into a single package (system) of models, on the basis of which system modelling is carried out, in order to optimize the unit as a whole, it is necessary to analyze the advantages and disadvantages of each model that can be built, to develop criteria for selecting models by cost, by purpose, by accuracy, etc., as well as determine the principles of combining the developed models into a package.

For this purpose, various types of models of the main units of the catalytic reforming unit of the LG unit have been pierced. Based on the results of studies of the specificity of the process and units of the catalytic reforming unit [136–138], experimental data and expert demand, and analysis of approaches to modelling such or similar units, an assessment of possible types of models of the main units of the catalytic reforming unit of the LG unit was carried out. The result of this analysis (model assessment) is presented in the form of **Table 2.1**. A five-point scale was used to assess (rank) the types of models.

Table 2.1 Analysis of the types of models of the main units of the catalytic reforming unit of the LG unit

No.	The main units of the catalytic reforming unit	Criterion	Types of models			
			Deter-ministic	Statis-tical	Fuzzy	Com-bined
1.1	Reactors: R-2, R-3, R-4, R-4a	Availability of the necessary information	2	4	4	5
1.2		Development cost	1	4	3	3
1.3		Degree of adequacy	4	3	4	4
1.4		Suitability for the intended purpose	3	3	4	5
1.5		Possibility of package	4	3	3	3
			14	17	18	**20**
2.1	Reforming furnace F-1	Availability of the necessary information	3	5	4	5
2.2		Development cost	2	4	4	4
2.3		Degree of adequacy	5	4	4	4
2.4		Suitability for the intended purpose	4	5	4	4
2.5		Possibility of package	4	4	4	4
			18	**22**	**20**	**21**
3.1	Reforming separators: HP S-7, HP S-8 and Circulating gas S-9	Availability of the necessary information	4	5	4	5
3.2		Development cost	3	4	4	4
3.3		Degree of adequacy	5	4	4	4
3.4		Suitability for the intended purpose	4	5	4	4
3.5		Possibility of package	4	4	4	4
			20	**22**	**20**	**21**
4.1	Heat exchangers T-6 and refrigera-tors RC-6, RC-106	Availability of the necessary information	4	5	4	5
4.2		Development cost	3	5	4	3
4.3		Degree of adequacy	5	5	4	5
4.4		Suitability for the intended purpose	5	4	5	5
4.5		Possibility of package	5	4	4	4
			22	**23**	**21**	**22**
5.1	Reforming filters A-14, A-15	Availability of the necessary information	4	4	4	5
5.2		Development cost	5	4	4	4
5.3		Degree of adequacy	5	4	4	5
5.4		Suitability for the intended purpose	5	5	5	4
5.5		Possibility of package	5	5	4	4
			24	22	21	22

Note: Estimation (ranking) on a point scale (1–5), where 1 is the lowest grade; 5 is the highest grade. The estimates are fuzzy, i.e. fuzzy numbers.

As the main criteria for comparing various types of models by which they are assessed, the following are highlighted: the availability of the necessary information to build a model of the corresponding type, the cost (difficulty) of developing a model, the degree of adequacy of the model, the applicability of these models for their intended purpose (in our case, for multicriteria optimization under conditions uncertainty) and the possibility of combining a model of this type into a single package for the purpose of systemic modelling of the unit as a whole.

Table 2.1 reflects the estimates for each type of model of the main units of the catalytic reforming unit of the LG unit, obtained on the basis of processing the results of the analysis.

Based on the information given in the above table, it is possible to select the type of unit models of the unit according to the specified criteria. The results of the study of the operation of the complex of technological units of the catalytic reforming unit of the LG unit and a possible set of their models show that due to the complexity of the units, the difficulty of studying the processes occurring in them and the impossibility of obtaining reliable data, the building of deterministic models for the main units (reforming reactors R-2, R-3, R-4, 4a, furnaces F-1) is practically impossible or economically inexpedient. For heat exchangers for building models of this type, according to the estimates of the above criteria, it is advisable to develop deterministic models.

Statistical (stochastic) models of the P-1 furnace and the S-7, S-9 separators of the catalytic reforming unit are relatively easy to build, convenient for combining them into a single system of models, and are suitable for solving problems of plant optimization. Based on the results of the study, it can be concluded that the building of statistical models is optimal for furnaces and separators.

At the operating DM of the Atyrau Refinery, the collection of reliable statistical information for the building of regression models of reforming reactors R-2, R-3, R-4, 4a is complicated by the absence or shortage of special industrial devices and the low reliability of the available means.

In this regard, the methods of expert assessments [139–141] were chosen as more effective means that supplement the missing data based on qualitative information (knowledge of specialists), and methods based on the theory of fuzzy sets (see the proposed algorithm for synthesizing fuzzy models) and combined methods. The adequacy of such models with the correct formalization and use of knowledge, the experience of expert specialists is high enough, and they can also be effectively used in modelling in order to optimize the reforming process in an interactive mode.

In practice, in order to build models with a shortage of information, it is necessary to use available information of any nature. Models of technological units obtained on the basis of such data will be called combined. They can be obtained using various combinations of available data and are focused on taking into account the merits of the types of models discussed above. However, the building of combined models may be impractical due to the need for a stage of organization, research and experiments of various nature, as well as preliminary processing of the collected data.

When developing models of technological units that are part of a single technological unit, a decomposition approach is often used, according to which models of individual subsystems and elements are built separately, and often the issue of further combining the resulting models into a single package is not taken into account. Such a particular solution to the issue does not give the final desired effect and positive result. Because the modelling and optimization of a separate unit of the technological complex of the catalytic reforming unit in the full sense is impossible, since the operation of this unit is associated with the work of the rest of the units of the complex.

Therefore, to fully solve the problems of modelling the complex of the technological complex, which are the objects of the catalytic reforming unit of the LG unit and other plants of the oil refining industry, it is necessary to create a package of plant models taking into account the relationships between the units, i.e. the outputs of some models can be the inputs of others, and the outputs of these models can be the inputs of older and other models.

With the use of such a package of models, it is possible to carry out system modelling of a technological complex, i.e. interconnected technological units as a whole and find the optimal operating modes of the technological complex, which will allow the intensification of the technological process. As a result of system modelling of the technological complex, it is possible to identify the «bottlenecks» of the unit, the solution of which will allow increasing the capacity and productivity of the technological complex and process.

The combination of individual models of units into a package is carried out in accordance with the course of the technological process at the complex. In this case, the outputs of one model are the inputs of another. For example, in the catalytic reforming unit, the modelling results of the R-2 reactor are the initial data for modelling the operation of the 2nd stage of the F-1 multi-chamber furnace, the modelling results of this furnace stage are the input data for the R-3 reactor models, and the output results of the R-3 models are the initial data for the 3rd stage of the F-1 furnace, the output results, which are the initial data for the R-4, 4a reactors. Thus, the main criteria for choosing types of aggregate models, in addition to the adequacy and effectiveness of their use in a computer modelling and optimization system, also includes the simplicity of their integration into a system, i.e. mutual correspondence of output and input variables of related models.

The optimal operating parameters of various units of the catalytic reforming unit cannot be determined a priori in the general case, since the parameters influencing the process can change. In this regard, the optimization of the reforming process with the help of online computer systems has a great advantage. For system modelling of the unit in the dialogue mode, it is necessary to have a fairly simple mathematical model of the main units, since the computer time spent on modelling should be minimized, since any optimization algorithm repeatedly refers to the modelling subroutine, and the response time of the control system for issuing control recommendations should also be small. Therefore, when building models for a catalytic reforming unit, as the most acceptable approach, this work uses a technique according to which, first, based on the results of studies of each unit and on the basis of the collected data, a model of this unit is built. Then these models are combined into a single package of models for the purpose of describing the process as a whole.

2.3 METHODOLOGY FOR BUILDING MATHEMATICAL MODELS OF INTERCONNECTED TECHNOLOGICAL UNITS OF CHEMICAL TECHNOLOGICAL SYSTEMS IN CONDITIONS OF SHORTAGE AND INDISTINCTNESS OF INITIAL INFORMATION

To build mathematical models of interconnected units of a chemical-technological system, it is necessary to develop a methodology based on methods of system analysis, using fuzzy information and other available data. The available initial information can be statistical, experimental data, theoretical information and expert information.

The methodology for the development of CTS mathematical models, consisting of interconnected objects, based on the available information of a different nature, includes the following main points:

1. Research and system analysis of CTS: collection and processing of available information, determination of the purpose of modelling.

2. Taking into account the purpose of modelling, determine and select criteria for assessing and comparing the types of models for each unit of the technological complex under study.

3. According to the selected criteria, conduct an expert assessment of each type of model for the aggregates and, using the integrated criterion, determine the effective type of model for each aggregate. This stage can have the following sub-stages:

3.1 If the theoretical information describing the operation of a separate unit is sufficient and the deterministic model will be optimal according to the integrated criterion, then a deterministic model is built for this unit on the basis of analytical methods.

3.2 If the statistical data describing the operation of the unit is sufficient, or they can be collected on the basis of experiments, as well as by the integrated criterion, the experimental-statistical model is optimal, then on the basis of experimental-statistical methods, a statistical model of the unit is developed.

3.3 In practice, there may be a case when the theoretical and statistical information describing the operation of the investigated unit is insufficient, and the collection of such information is impossible or economically inexpedient. In this case, if there is fuzzy information and, according to the integrated criterion, a fuzzy linguistic model is optimal, then using the methods of fuzzy set theories, a fuzzy or linguistic model of the object is built. For this, the transition is carried out to point 4.

3.4 If theoretical, statistical data and fuzzy information describing the operation of the TS unit is not enough or their collection is economically inexpedient, then a combined (hybrid) model is built [72]. In this case, the combined model is developed on the basis of available information of a different nature (theoretical, statistical, fuzzy). To do this, to describe a specific parameter object, various combinations of sub-clauses 3.1, 3.2, 3.3 are used.

4. Determination and selection of input $\tilde{x}_i \in \tilde{A}_i,\ i=\overline{1,n}$ and output $\tilde{y}_j \in \tilde{B}_j,\ j=\overline{1,m}$ parameters (variables) of the object, describing, respectively, input, operating parameters, and the quality of the object. These parameters are necessary for building a model and can be linguistic variables: $\tilde{A}_i \in X$, $\tilde{B}_j \in Y$ – fuzzy subsets, X, Y – universal sets of input and output parameters. The input parameters can be crisp, i.e. $x_i \in X_i,\ i=\overline{1,n}$.

5. If, $x_i \in X_i,\ i=\overline{1,n}$, i.e. input parameters are criso, then determine the structure of fuzzy models $\tilde{y}_j = \tilde{f}_j\left(x_1,\dots,x_n,\tilde{a}_0,\tilde{a}_1,\dots,\tilde{a}_n\right),\ j=\overline{1,m}$ (structural identification of models). For example, the structure of the model can be defined as fuzzy multiple regression equations:

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{n} a_{ij}x_{ij} + \sum_{i=1}^{n}\sum_{k=i}^{n} a_{ikj}x_{ij}x_{kj},\ j=\overline{1,m}.$$

6. Based on the methods of expert assessment with the involvement of decision makers, determine the term-sets $T\left(\tilde{X}_i,\tilde{Y}_j\right)$ that describe the parameters of the simulated object.

7. Building of the membership function of fuzzy parameters of the object: $\mu_{A_i}\left(\tilde{x}_i\right)$, $\mu_{B_j}\left(\tilde{y}_j\right)$.

Based on the experience of modelling technological objects of oil refining production in a fuzzy environment, the following adaptable structure of the membership function can be recommended:

$$\mu_{B_j}^{p}\left(\tilde{y}_j\right)=\exp\left(Q_{B_j}^{p}\left|\left(y_j-y_{mdj}\right)^{N_{B_j}^{p}}\right|\right),$$

where $\mu_{B_j}^{p}\left(\tilde{y}_j\right)$ – membership function describing the output fuzzy parameters to the fuzzy set $\tilde{B}_j$; p – number of quantum (sampling interval); $Q_{B_j}^{p}$ – parameter (coefficient) that determines the level of fuzziness, which is determined when identifying the membership function; $N_{B_j}^{p}$ – coefficients defining the domain of definition of terms of the membership function of fuzzy parameters and allowing to change the shape of the membership function graph; y_{mdj}^{p} – fuzzy variable that most closely matches a given term on the quantum p. This variable is determined from the following condition $\mu_{B_j}\left(y_{mdj}^{p}\right)=\max\limits_{j}\mu_{B_j}\left(y_j\right)$.

8. If the input and output parameters are fuzzy, then it is necessary to determine the relationship between the input and output linguistic variables, i.e. fuzzy mappings R_{ij} between $\tilde{x}_i$ and $\tilde{y}_j$.

For the convenience of using fuzzy mapping in the calculation, the matrix of connections with membership functions is determined:

$$\mu_{R_{ij}}\left(\tilde{x}_i,\tilde{y}_j\right)=\min\left[\mu_{A_i}\left(\tilde{x}_i\right),\,\mu_{B_{ji}}\left(\tilde{y}_j\right),\,i=\overline{1,n},\,j=\overline{1,m}\right].$$

Then a linguistic model is built with a general structure:

$$IF\ \tilde{x}_1\in\tilde{A}_1\left(\tilde{x}_2\in\tilde{A}_2\left(,\ldots,\left(\tilde{x}_n\in\tilde{A}_n\right),\ldots,\right)\right)\ THEN\ \tilde{y}_j^{M}\in\tilde{B}_j,\ j=\overline{1,m}$$

and go to Step 10.

9. If the condition of clause 5 is satisfied, then using the set of level α and the modified least squares method, determine the values of the fuzzy coefficients $\left(\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n\right)$ (parametric identification) and go to clause 11.

10. If the condition of clause 8 is satisfied, then on the basis of the compositional inference rule determine the fuzzy values of the object's output parameters $\tilde{B}_j=\tilde{A}_i\circ R_{ij}$, then the numerical values of the output parameters are determined from the fuzzy solutions.

At this point, using the compositional inference rule, the output parameters of the object are determined, which determine the quality of its work, for example, using the maximin product.

Let $\tilde{x}_i^{*}$ denote the values of the input fuzzy parameters of the object, assessed by experts. In this case, the set of current values of the input parameters is defined as a fuzzy set, in which the membership functions of the input parameters will be maximal: $\mu_{A_i}\left(\tilde{x}\right)=\max\left(\mu_{A_i}\left(\tilde{x}_i^{*}\right)\right)$. Then the fuzzy values of the output variables are determined in the form of membership functions, expressing the maximal product:

$$\mu_{B_j}\left(\tilde{y}_j^{*}\right)=\max\left\{\min_{x_i\in X_i}\left[\mu_{A_i}\left(\tilde{x}_i^{*}\right),\mu_{R_{iij}}\left(x_i^{*},\tilde{y}_j\right)\right]\right\}.$$

The quantitative values of the output parameters can be determined using the following expression:

$$y_j^c = \arg\max_{\ddot{y}_j^*} \mu_{B_j}\left(\tilde{y}_j^*\right),$$

i.e., the values of the output parameters are selected, in which the membership functions and reach the maximum values (if the membership functions are normal then 1).

11. Checking the condition of the model adequacy:

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

where y_j^M – the calculated (model), and y_j^E – the experimental (real) values of the output parameters of the object, R_D – the permissible deviation. If the adequacy condition is met, then the model is recommended for modelling and determining the optimal operating modes of the object. Otherwise, the reason for the inadequacy of the model is determined and the transition is processed to the corresponding points of the described methodology. In this case, the reason for the inadequacy of the model can be: not including some parameters in the model that significantly affect the process; incorrect structural and/or parametric identification of the model, etc.

The discussion of the results. The proposed methodology for the development of mathematical models of interconnected objects in conditions of scarcity and indistinctness of initial information is based on methods of system analysis, expert assessment, fuzzy set theories, as well as on traditional methods of model development. The technique allows, in conditions of uncertainty due to the deficit and fuzziness of available information, to build a system of mathematical models based on available information of a different nature (theoretical, statistical, fuzzy), including combining available information. At the same time, depending on the nature of the information used in the building of models, various types of models can be developed (deterministic, statistical, fuzzy, linguistic and combined).

In order to determine the most suitable type of model for each unit of the technological system, it is necessary to carry out a system analysis, and an assessment of each type of model according to the selected comparison criterion. Such criteria can be, for example, the availability of the initial information for the development of the corresponding type of model; development cost; the adequacy of the model, etc. Since the developed models still need to be combined into a single package of models for systemic modelling of the operation of a technological unit, one should take into account the possibility of combining the selected type of model into a package.

Thus, the developed methodology in conditions of a deficit and indistinctness of the initial information allows to create a system of mathematical models of interconnected objects based on the available information of a different nature. This approach can be effectively applied in the development of mathematical models of complex technological systems, which are often characterized by uncertainty. In this case, the condition for the applicability of the proposed methodology is the availability of experienced specialists, decision makers (experts), who are available for many functioning technological objects. The mathematical apparatus for collecting, formalizing and applying fuzzy information from experts, decision makers is the methods of fuzzy set theories and expert assessment.

2.4 METHODS FOR THE SYNTHESIS OF MODELS OF CHEMICAL-TECHNOLOGICAL OIL REFINING SYSTEMS BASED ON FUZZY INFORMATION

In this section of the work, a complex of technological units of the catalytic reforming unit is investigated as an object of modelling and optimization. An algorithm for the synthesis of mathematical models of the investigated complex in a fuzzy environment is proposed.

The technological complex of catalytic reforming and the tasks of modelling the modes of its operation are characterized by complexity. The complexity of the object of research is manifested in a significant number and variety of parameters that determine the course of processes, in a large number of internal connections between parameters, in their mutual influence, in an unformalized action of a person participating in the control loop. In addition, when formalizing and solving problems of optimizing the reforming process, a number of problems arise associated with a variety of criteria that determine the quality of an object.

The multi-criteria nature of the systems under study makes it difficult to develop a mathematical description of the processes on the basis of which the optimization procedure is carried out. Due to the unreliability, shortcomings or lack of the necessary means for collecting and processing statistical data, the information collected to describe the studied complex may turn out to be largely incomplete, rather vague. Conducting special experiments to collect missing information, even if they are possible, often turns out to be economically impractical. The main source of information in these situations is a person (specialist-expert, decision maker: technologist, operator), who gives an fuzzy description of the problem, i.e. there is a problem of uncertainty associated with the fuzziness of the initial information.

In this monograph, new approaches and methods for the development of mathematical models of a technological complex are proposed and used, in the presence of the problems of multi-criteria and fuzzy initial information discussed above.

As it is known, when modelling and optimizing complex systems under uncertainty, a probabilistic approach based on the methods of probability theory and mathematical statistics is used. However, in practice, in the presence of uncertainties, the axioms of the probability theory are not always fulfilled, which shows the inappropriateness of the application of these methods. Moreover, in cases where there is reason to believe that processes or systems behave according to probabilistic laws, the lack of information, the impossibility or high cost of obtaining reliable statistical information push to other ways of describing real processes in production systems, to the development of non-statistical, for example, fuzzy methods. modelling objects. One of the promising ways in this direction is based on the methods of the theory of fuzzy sets [58, 59, 142–144].

Thus, the problem of uncertainty can be solved by creating a mathematical apparatus for describing and researching fuzzy objects.

The following approaches to modelling objects can be distinguished that satisfy these requirements, which are based on the methods of the theory of fuzzy sets [48]:

1. An approach based on the building of statistical models of objects with fuzzy coefficients based on the modification of regression analysis methods. The models obtained on the basis of this approach are successfully used in the modelling and control of a number of technological objects of the oil refining industry.

Let's suppose that as a result of observing an object or a performed experiment, the values of the input parameters are obtained Lx_i $\left(x_{il},\, i=1,n,\, l=\overline{1,L}\right)$, and the corresponding fuzzy values of the output parameters $\tilde{y}_j^E$ $\left(y_{jl},\, j=\overline{1,m},\, l=\overline{1,L}\right)$ are assessed by experts, i.e. the input parameters of the system are measurable and their quantitative values are available, and the output parameters are fuzzy, i.e. assessed (measured) by specialist experts.

To build a mathematical model of this object, it is necessary to solve the following two stages of the identification problem:

a) select the structure of the function (structural identification):

$$\tilde{y}_j^M = \tilde{f}_j \left(x_1,\ldots,x_n,\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n\right),\ j=\overline{1,m}, \tag{2.1}$$

approximating function $\tilde{y}_j = f_j\left(x_1,\ldots,x_n\right)$.

At this stage, a qualitative analysis of the object is of decisive importance, as a result of which the main parameters affecting the functioning, their interrelations are identified, and a method is selected for identifying the structure of the model.

b) determine the estimates of the parameters of the selected function (2.1) (parametric identification), for example, the values of fuzzy coefficients $\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n$. For such an assessment, one can use the criterion of minimizing the deviation of the fuzzy values of the output parameter $\tilde{y}_j^M$ obtained by model (2.1) from its sample fuzzy values obtained on the basis of expert assessment $\tilde{y}_j^E$.

$$\tilde{R}_j = \min\sum_{l=1}^{L}\left(\tilde{y}_{jl}^E-\tilde{y}_{jl}^M\right)^2 = \min\sum_{l=1}^{L}\left(\tilde{y}_{jl}^E-\tilde{f}_j\left(x_1,\ldots,x_n,\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n\right)\right)^2. \tag{2.2}$$

At the second stage, the main issue is the choice of a method for estimating unknown parameters that provides the necessary properties of the object under study.

In this approach, mathematical models obtained taking into account the fuzziness of the initial information have the following general form:

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{n}\tilde{a}_{ij}x_{ij} + \sum_{i=1}^{n}\sum_{k=i}^{n}\tilde{a}_{ikj}x_{ij}x_{kj} + \ldots,\, j=\overline{1,m}, \tag{2.3}$$

where $\tilde{y}_j$ – fuzzy output parameters of the system (local criteria); x_{ij}, x_{kj} – input measured parameters of the modeled system (control actions); $\tilde{a}_{0j}, \tilde{a}_{ij}, \tilde{a}_{ikj}$ – assessed fuzzy coefficients.

Using the concept of level set a allows to reduce fuzzy regression equations to a system of ordinary regression equations. This approach makes it possible to apply classical regression methods to solve the problems discussed above.

2. An approach based on the use of logical rules for conditional inference, for example, in the following form:

$$If\ \tilde{x}_1 \in \tilde{A}_1\left(\tilde{x}_2 \in \tilde{A}_2,\ldots,\left(\tilde{x}_n \in \tilde{A}_n\right),\ldots,\right), Then\ \tilde{y}_j \in \tilde{B}_j, j=\overline{1,m}, \tag{2.4}$$

where $\tilde{x}_i$, $i=\overline{1,n}$, $\tilde{y}_j$, $j=\overline{1,m}$ – respectively, the input and output linguistic variables of the object, affecting the technical, economic and environmental performance of the object; $\tilde{A}_i$, $\tilde{B}_j$ – fuzzy subsets characterizing $\tilde{x}_i$, $\tilde{y}_j$.

Here, both the input and output parameters of the system $\left(\tilde{x}_i,\tilde{y}_j\right)$ are fuzzy, that is, they can be linguistic variables. The advantage of this approach is the possibility of using it when modelling objects for which the collection of statistical information $\left(\tilde{x}_i,\tilde{y}_j\right)$ is very expensive, difficult or impossible. In this case, the obtained fuzzy models are the result of processing an expert survey of experts (technologists, operators, decision makers), operating, as a rule, with information of a qualitative nature (experience, knowledge). Such information, provided that there is sufficient competence of expert specialists, makes it possible to take into account the whole range of complex internal interrelations of object parameters in the obtained models.

The advantages of methods for building fuzzy models include: the following they allow to obtain effective models of an object in conditions of uncertainty, when traditional approaches do not give significant results; the models obtained on the basis of these approaches take into account the internal, meaningful connections of the main parameters of the system, which are not subject to formalization. However, when building fuzzy models, specific problems arise, for example, those associated with conducting an expert survey, building a membership function of fuzzy parameters, determining the structure of a conditional inference, etc.

3. When building models of a system that is a complex of interconnected units of various types (technological units) with different initial information, it is necessary to use combined information. In this case, models of individual objects in the system can be built by different methods, and the possibility of combining these models into a package for modelling the operation of the system as a whole should be taken into account. In practice, in the study of a certain object, statistical data for assessing some parameters may be sufficient, and for other parameters – insufficient or even absent. The parameters of such objects are estimated by methods based on the use of information of a different nature and combining the above methods and traditional approaches to the analysis of systems.

As a result of the analysis and generalization of possible approaches to modelling complex objects with indistinct initial information in this work, methods for the synthesis of models of a technological complex with fuzzy input and output parameters have been developed, which uses logical rules of conditional inference and implements the second approach of fuzzy modelling and allows to build linguistic models in a fuzzy environment. Here are the main stages of the proposed algorithm.

On the basis of the above described approaches to the development of models in a fuzzy environment, let's present the main stages of the proposed methods for synthesizing models, taking into account the fuzziness of the initial information, and then explain their content.

Let's offer the following methods for building models taking into account the fuzziness of the initial information.

Fuzzy model synthesis method.

1. Select the input (mode – control) $x_i \in X_i, i = \overline{1,n}$ and output $\tilde{y}_j \in Y_j, j = \overline{1,m}$ parameters of the object necessary for building the model.

2. Collect information and, on the basis of an expert procedure, determine the term-set $T(X,Y)$ of fuzzy parameters describing the state of the object.

3. Determine the structure of fuzzy equations $\tilde{y}_j = \tilde{f}_j\left(x_1,\ldots,x_n,\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n\right)$, $j = \overline{1,m}$ (solving the problem of structural identification).

4. Build the membership function of the fuzzy parameters of the object and the coefficients of the model.

5. Estimate fuzzy coefficients $\left(\tilde{a}_0,\tilde{a}_1,\ldots,\tilde{a}_n\right)$ of functions $\tilde{y}_j$ (parametric identification).

6. Check the conformity of the model to real data (model adequacy). If the model is inadequate, find out the reason and return to the appropriate point.

This method implements the idea of the first approach to the synthesis of models based on fuzzy information described in the previous subsection and allows to build models with crisp input and fuzzy output parameters of the object. Let's give explanations for some points of the given method.

In the first paragraph, depending on the required accuracy, the most informative variables are selected that characterize the quality of the object's work. For convenience, the ranges of variation of indistinctly described parameters are set in the form of segments, indicating the minimum $\left(y^{\min}\right)$ and maximum values $\left(y^{\max}\right)$. These segments, depending on the discussion of expert experts, are divided into several intervals (quanta), for example:

$$y_j^{\min} = y_j^1 < y_j^2 < \ldots < y_j^l = y_j^{\max}.$$

To build a term-set of states (point 2), each quantum of the selected parameters is characterized by the corresponding fuzzy terms. For example, if $\tilde{y}_j$ is the quality of the products produced at the facility, then they can be described through the terms:

$$\tilde{y}_j = \{\text{low, below average, average, above average, high}\}.$$

The accepted term-set is a set of values of linguistic variables that describe the operation of an object. Each sampling interval obtained in item 1 is characterized by a certain term, this term corresponds to a fuzzy set, which is described by the membership function at the corresponding gradation level.

Determination of the structure of fuzzy multiple regression equations (point 3) and identification of their fuzzy coefficients (point 5) is carried out in the following way. The problem of structural identification is solved based on the results of a systemic study of the object, using, for example, the idea of the method of sequential inclusion of regressors, the essence of which is the sequential inclusion of successive regressors until the model is adequate to real data. For parametric identification, it is possible to use a fuzzy analogue of the least squares method.

The building of the membership function of fuzzy parameters (point 4) is one of the main stages in modelling complex objects using the methods of the theory of fuzzy sets. The known methods for building the membership function are divided into direct and indirect methods. In direct methods, the degree of membership is assigned directly by a person or a set of standard graphs is used, and experts are involved to determine the parameter. In indirect methods of building the membership function, the assessments received from the expert are processed in accordance with a certain algorithm in order to reduce the level of subjectivity of expert assessments. In practice, to identify the structure of a function on the basis of certain methods, a graph of the curve of the degree of membership of one or another parameter to the corresponding fuzzy set is built. On the basis of the resulting graph, a function is selected that best approximates it. After that, the parameters of the selected function are identified.

Determination of the structure of fuzzy multiple regression equations (point 3) and identification of their fuzzy coefficients (point 5) is carried out in accordance with stages 1 and 2 given above in the description of the first approach to the synthesis of models based on fuzzy information. The problem of structural identification is solved according to the results of a systematic study of the object, using, for example, the idea of the method of sequential inclusion of regressors, the essence of which is the sequential inclusion of successive regressors (linear factors, factors of pair interaction, the nonlinear part with an increase in the degree) until the conditions for the adequacy of the model to real data are met. For parametric identification, it is possible to use a fuzzy analogue of the least squares method.

The task of the final stage of the method (point 6) is to check the conformity of the model to the object. A model is considered adequate to an object if the characteristics of the object found with its help coincide with a given degree of accuracy with real data obtained experimentally at the object itself.

The block diagram of the algorithmization of the described method is shown in **Fig. 2.2**.

As a rule, the value of the mismatch between the calculated (model) y^M and real (experimental) data y^E is used as an adequacy criterion, which is a measure of the conformity of a model to an object; $R=\left|y^M-y^E\right|$. In addition, the value of the admissible mismatch level is selected – R_D. The model is considered adequate if $R=\left|y^M-y^E\right|R_D$.

In case of inadequacy, the reasons for inadequacy are determined and a return to the appropriate point of the method is carried out to refine the model.

The next method uses the idea of a logical rule of conditional inference and is proposed to build a linguistic model with fuzzy values of the input and output parameters of the object.

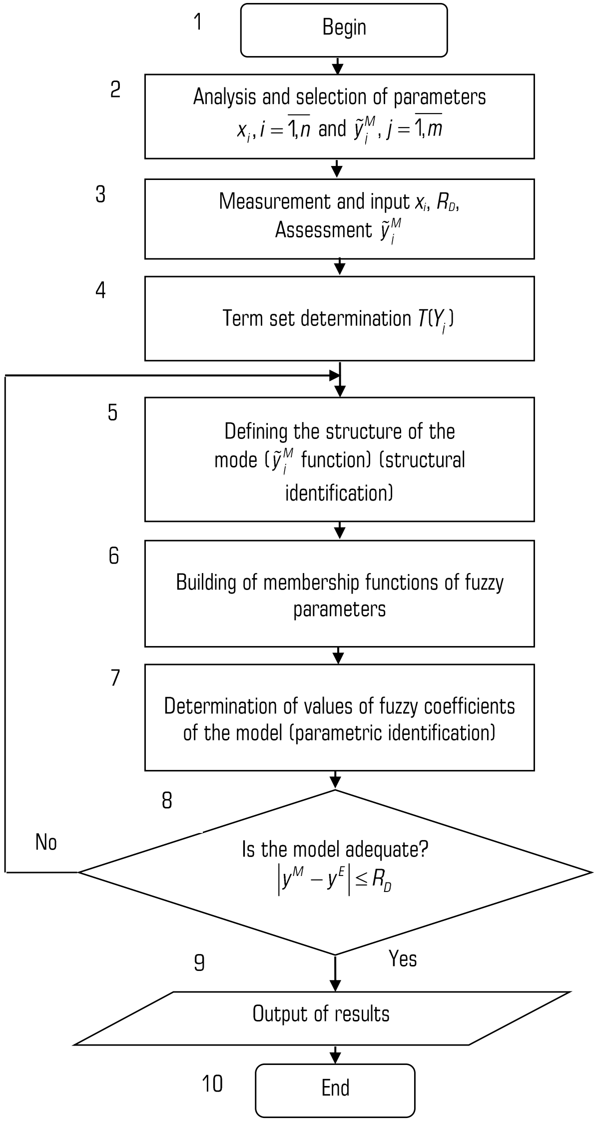


Fig. 2.2 Block diagram of the algorithmization of the fuzzy model synthesis method

Method for synthesizing a linguistic model. This method implements the idea of the above described second approach to the synthesis of models based on fuzzy information. Some points of this method (1, 2 and 6) are similar to the corresponding points of the fuzzy model synthesis method, but take into account the fuzziness of the input parameters – $\tilde{x}_i$, $i = \overline{1,m}$:

1. Select the input $\tilde{x}_i \in X_i$, $i = \overline{1,n}$ and output $\tilde{y}_j \in Y_j$, $j = \overline{1,m}$ parameters of the object, necessary for building the model, which are linguistic variables (X_i, Y_j – universal sets).

2. On the basis of expert assessment, estimate the values of the parameters $\tilde{x}_i$, $\tilde{y}_j$ and build the term-set $T(X_i, Y_j)$.

3. Build membership functions of fuzzy parameters $\mu_{\tilde{A}_i}(\tilde{x}_i)$, $\mu_{\tilde{B}_j}(\tilde{y}_j)$ ($\tilde{A}_i$, $\tilde{B}_j$ – fuzzy subsets $\tilde{A}_i \subset X_i$, $\tilde{B}_j \subset Y_j$).

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

5. Determine the fuzzy values of the output parameters of the object and select their numerical values from the fuzzy set of solutions.

6. Check the conditions for the adequacy of the model. If the model is inadequate, find out the reason and return to the appropriate point to refine the model.

Let's consider some details of the described method for synthesizing a linguistic model. The linguistic model of the object is built on the basis of the results of processing expert information (paragraph 4). For convenience, it can be drawn up in the form of a table, where the various values of the operating parameters and the values $\tilde{y}_j^M$ corresponding to these options are not clearly indicated. The table should be filled using the selected term-set. On the basis of the model obtained in this way, fuzzy mappings R_{ij} are formalized, which determine the relationship between linguistic variables: $\tilde{x}_i$, $\tilde{y}_j$. It is convenient to formalize such a fuzzy mapping by the method of logical assessment. In this case, based on expert information, using expert information, using term sets $T(X_i,Y_j)$ of linguistic variables, a complete description of all possible situations is given. This description, which is called a linguistic model, consists of a set of nested logical rules of the form (2.4):

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

Fuzzy mappings for quantum p are defined as: $R_{ij}^p = A_i^p \times B_j^p$. For the convenience of using fuzzy mapping R_{ij} in calculations, it is necessary to build matrices of fuzzy relations – $\mu_{R_{ij}}\left(x_i, y_j^M\right)$ for example, in the general case for selected quanta:

$$\mu_{R_{ij}}^p\left(x_i, y_j^M\right) = \min\left[\mu_{A_i}^p\left(x_i\right), \mu_{B_j}^p\left(y_j^M\right)\right],\ i = \overline{1,n},\ j = \overline{1,m}. \qquad (2.5a)$$

The fifth point of the method is to apply the compositional inference rule:

$$B_j = A_i \circ R_{ij},$$

where $A_i \subset X$, $B_j \subset Y$, X,Y – universal sets.

Using this rule, it is possible to calculate the output variables, for example, by the expression:

$$\mu^{p}_{B_{ij}}\left(y'_j\right)=\max_{x_i\in X_i}\left\{\min\left[\mu_{A_i}\left(x^{*}_i\right),\mu_{R_{ij}}\left(x_i,y^{M}_j\right)\right]\right\}. \tag{2.5b}$$

Let y^{*}_j – the values of the regime parameters assessed by experts, then the desired set, which owns the current values of the input variables, is defined as the set for which the values of the regime parameters have the highest values of the membership function:

$$\mu_{A_i}\left(\tilde{x}^{*}_i\right)=\max\left(\mu_{A_i}\left(\tilde{x}_i\right)\right). \tag{2.5c}$$

Specific numerical values of the output parameters y^{*}_j from the fuzzy set of solutions are determined from the following relation: $y^{M}_j=\arg\max_{y'_i}\mu_{B_j}\left(y'_i\right)$, $j=\overline{1,m}$, i.e. those values of the output parameters are selected for which the maximum of the membership function is achieved.

In the case when the number of terms defining the set of input and output parameters is large, it is difficult for a person (expert) to estimate a large number of necessary degrees of membership, and the subtask of determining (interpolating) intermediate values arises, i.e. synthesis of new terms from a small number of available terms. An algorithm for interpolating a set of terms in a fuzzy environment was proposed in [69] and described below.

The building of the membership function of fuzzy sets (parameters) (point 4) is carried out similarly to point 4 of the fuzzy model synthesis method. The practice of building membership functions has shown that the membership functions of fuzzy sets describing the accepted terms can be approximated with an exponential rather accurately, for example, for the membership function analytically it has the form:

$$\mu^{p}_{B_j}\left(\tilde{y}^{M}_j\right)=\exp\left(Q^{p}_{B_j}C^{p}_{B_j}\left|\left(y_j-y^{p}_{md_j}\right)^{N^{p}_{Bj}}\right|\right), \tag{2.5d}$$

where $\mu^{p}_{B_j}\left(\tilde{y}^{M}_j\right)$ – function (degree) of parameters $\tilde{y}^{M}_j$ belonging to a fuzzy set $\tilde{B}_j$, characterizing the values of the output parameters; p – the number of the gradation (quantum); $Q^{p}_{B_j}$ – parameter that is found during identification of the membership function and determines the level of fuzziness; $C^{p}_{B_j}$, $N^{p}_{B_j}$ – coefficients for changing the domain of definition of terms and the shape of the graph of the membership function of fuzzy parameters; $y^{p}_{md_j}$ – fuzzy variable most corresponding to the given term (in the quantum p), for which $\mu^{p}_{B_j}\left(y_{md_j}\right)=\max_{j}\mu^{p}_{B_j}\left(y_j\right)$. This approach is justified if the membership graph of the function has a sharp shape in the region of its maximum. If the maximum value of the function is reached on a segment (the graph of the membership function in the region of its maximum contains many points that are close in value), then their average value is chosen as the numerical values y^{*M}_j.

The block diagram of the algorithm for the implementation of the linguistic model synthesis method is shown in **Fig. 2.3**. Let's give a brief description of algorithms for solving subtasks arising from the application of the above described methods of developing fuzzy models.

The main subtasks include: the problem of building accessory functions and the problem of synthesizing new meanings of terms in a fuzzy environment. The dialog algorithms described below for solving these problems work on the basis of information received from a person and are human-machine procedures. The dialog algorithm for building the membership function proposed in this work is described below.

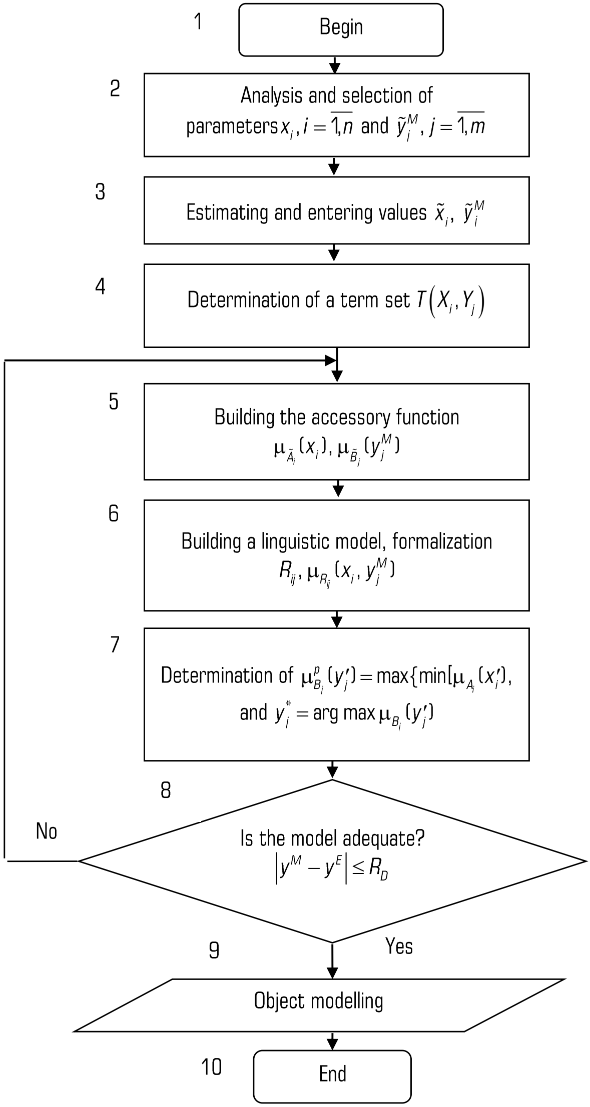


Fig. 2.3 Block diagram of the algorithm for the implementation of the linguistic model synthesis method

Algorithm for building accessory functions:

1. On the basis of expert assessment, determine the number and name of the parameters used for a fuzzy description of the object states: $\tilde{x}_i \in X_i,\ i=\overline{1,n}$ (input) and $\tilde{y}_j \in Y_j,\ j=\overline{1,m}$ (output).

2. Determine the segments on which the input and output parameters change: $\tilde{x}_i \in \left[x_i^{\min}, x_i^{\max}\right]$, $\tilde{y}_j^M = \left[y_j^{\min}, y_j^{\max}\right]$.

3. Specify the sets of terms $T(X,Y)$ for the description $\tilde{x}_i$, $\tilde{y}_j^M$.

4. Determine the carrier – the domain of definition of fuzzy sets for each of the terms.

5. The decision maker to assess the degrees of membership of the parameter values and normalize the estimates obtained, for example, by the expressions:

$$\mu_t^p\left(x_i\right)=\frac{M_t^p\left(x_i\right)}{\max\limits_t M_t^p\left(x_i\right)};\ \mu_t^p\left(y_j^M\right)=\frac{M_t^p\left(y_j^M\right)}{\max\limits_t M_t^p\left(y_j^M\right)},\ i=\overline{1,n};\ j=\overline{1,m},\ t=\overline{1,r},$$

where $\mu_t^p\left(x_i\right)$, $\mu_t^p\left(y_j^M\right)$ – respectively, the normalized estimate of the degree of membership of the input and output parameters of the object on the p-th sampling interval at point t; $M_t^p\left(x_i\right)$, $M_t^p\left(x_i\right)$, $M_t^p\left(y_j^M\right)$ – assessment of the affiliation degree, exhibited by an expert; r – the number of points at which the degrees of membership of the parameters are assessed $\tilde{x}_i$, $\tilde{y}_j^M$.

6. Approximate the obtained estimates by the analytical dependence (based on the graphical dependence $x_i(t)$, $\mu_i\left(x_i\right)$, $y_j^M\left(t\right)$, (for example, according to the formula (2.5)).

7. Identify the parameters of the obtained analytical dependence (coefficients $Q_{B_j}, C_{B_j}, N_{B_j}$ in expression (2.5d)).

In the fifth paragraph of the above algorithm, the following scheme for assessing the degrees of membership can be applied. To assess the degree of belonging of each fuzzy parameter to the selected terms (in point 3), the expert uses a point scale, for example [0–10], where 0 – the estimated point does not belong to the parameter, 5 – the average degree of membership, 10 – the point completely belongs to the parameter. Intermediate marks are set from the intervals 10÷5 [(less belongs) and 15÷10 [(more belongs). Then, the estimates of the degrees of membership obtained from the decision maker are normalized according to the expressions given in paragraph 5.

As already noted, in the practical use of the methods of the theory of fuzzy sets for the analysis and description of complex objects, the problem often arises of synthesizing new terms (determining the values of their membership functions), which more accurately describe the functioning of the object under study. The main reason for this problem is that for complex objects the number of terms (fuzzy variables) that determine the set of input and output parameters is large. This makes it difficult to define term sets describing the state of an object by means of an expert survey.

Let's formulate the problem of interpolation of intermediate (new) terms (values of fuzzy variables) in a fuzzy environment and present the main points of the algorithm for its solution.

Let L be a linguistic variable $L \subset X$, X – a universal set; $T(L)=\{T(l_1),\ T(l_2),\dots,T(l_n)\}$ – a term-set of the variable L, $l_i \in L,\ i=\overline{1,n}$. Task: for $\forall T\left(l_i\right)$ and, $T\left(l_j\right)$, $l_i, l_j \in L,\ i,j \in N,\ i \neq j$, N – a set of indices, find an intermediate (new) value $T\left(l_{ij}\right)$, $l_{ij} \in L$, $\left(T\left(l_i^*\right), T\left(l_i^*\right)\right)$.

Algorithm for interpolation of a set of terms in a fuzzy environment:

1. Build the initial set of terms $T(l_i) \in T(L),\ i = \overline{1,n}\ (n \leq 5)$.

2. Select the terms $T(l_i) \in T(L),\ T(l_j) \in T(L),\ i,j \in N$ between which it is necessary to find intermediate values of the linguistic variable $L - T(l_{ij})$ (or new values $T(l_i^*)$, $T(l_j^*)$), i.e. build membership functions for $\mu_L(l_{ij})$, ($\mu_L(l_i^*)$, $\mu_L(l_j^*)$).

3. Select modifiers that, on the basis of the main terms set by the DM, allow describing the content of the synthesized term – $T(l_j)$, $T(l_i^*)$, $T(l_j^*)$).

4. Perform operations on fuzzy sets corresponding to the selected modifier or their combinations, as a result of which the membership functions of the synthesized term are determined: $f\tilde{x} \in \tilde{A}(np)$, then $\tilde{y}_1 \in \tilde{B}_1(cp)$, $\tilde{y}_2 \in \tilde{B}_2(cp)$, $\tilde{y}_3 \in \tilde{B}_3(cp)$, or $\left(\mu_L\left(l_i^*\right) = \oplus\mu_L\left(l_i\right)\right)$, $\left(\mu_L\left(l_j^*\right) = \oplus\mu_L\left(l_j\right)\right)$, where is the operation on fuzzy sets.

The given algorithm for interpolation of a set of terms is based on the use of basic operations on fuzzy sets, for example, union, intersection, addition, product, concentration, stretching, etc.

Terms like «not», «or», «very», «more or less», and others are called modifiers or linkages. Applying a modifier to one of the primary terms converts it to another. The action of modifiers is to change the shape of the membership function or to shift the membership function along the axis without changing its shape.

2.5 CONDITIONS FOR THE ADEQUACY OF FUZZY MODELS AND AN APPROACH TO IDENTIFYING PARAMETERS OF FUZZY MODELS

Analysis of the functioning of various control systems in industry, based on fuzzy models, shows that their effectiveness is largely determined by the adequacy of fuzzy models to controlled objects.

The degree of adequacy of fuzzy models, first of all, depends on the depth of knowledge of the system under study and on the effectiveness of methods for formalizing and processing the knowledge of expert experts about an object or process.

To assess the adequacy of a fuzzy model to the original fuzzy data, criteria such as:

$$R_j = \min \sum_{j=1}^{m} \left(\tilde{B}_j - \hat{B}_j\right)^2 = \sum_{j=1}^{m} \left(\mu_{\tilde{B}_j}\left(\tilde{y}_j^M\right) - \mu_{\hat{B}_j}\left(\tilde{y}_j^M\right)\right)^2$$

characterizing the deviation of the membership functions of the original fuzzy sets $\mu_{\tilde{B}_j}\left(\tilde{y}_j^M\right)$, used in the formation of a fuzzy relation R_{ij}, from the membership functions of fuzzy sets $\mu_{\hat{B}_j}\left(\tilde{y}_j^M\right)$, calculated by the maximin product.

The inadequacy of the fuzzy model to the observed data of the object under study (initial fuzzy sets), in addition to the unreliability of expert information arising from improper organization of expert procedures or due to the incompetence of expert experts, is also associated with inaccurate implementation of the compositional inference rule. In this case, R_{ij} does not accurately reflect the given conditional logical statement.

The condition for the adequacy of a fuzzy model can be formulated as follows. Let the fuzzy relation be given: $R_{ij}=\bigcup_{i,j}\tilde{A}_i\times\tilde{B}_j$. If for each $\tilde{A}_i$ $B_j=A_i\circ R_{ij}$ is satisfied, then the compositional inference rule is strictly executed, i.e. the model is adequate, otherwise – approximately, which leads to a possible inadequacy of the model.

Approach to identifying parameters of fuzzy models. One of the problems in the development of mathematical models of production facilities, complex systems is the problem of identifying the parameters of the models, on the basis of which the analysis and management of these objects is carried out. The complexity of this task in the synthesis of models of production systems is associated with the fuzziness of the initial information.

Let's consider the proposed approach to identifying the parameters of fuzzy models. Since the estimated coefficients of such models are fuzzy, the methodology of the theory of fuzzy sets is used to identify them. The identification of the coefficients of fuzzy models is carried out in the following stages:

1. Based on the analysis of the object under study, a complete plan of «mental» experiments is drawn up. Planning is similar to planning experiments in mathematical planning, where instead of quantitative data, their approximate values are used in the form of fuzzy information.

2. Specialists-experts, on the basis of practical experience and knowledge, cut off plan options that are practically unrealizable or clearly lead to emergency situations (while they must justify the reasons for excluding each option from the plan).

3. For all other options, experts assess the impact of this ratio of input factors on the output parameters of the object (options for experience). The assessment is carried out on the basis of term sets that are preselected.

4. In case of uncertainty of experts in assessing some options, it is necessary to implement these options as possible in accordance with the plan and assess the results.

5. Since a group of experts should participate in assessing plans, the next step is to determine the degree of consistency of their opinions using a well-known method [10, 102, 103]. If the opinions of the experts mostly coincide, i.e. the values of the dispersion coefficient of concordance are close to 1 and $W_R \geq W_T$, then the end of the implementation of the plans and the transition to the processing of the results obtained, where W_R, W_T – respectively, the calculated and tabular values of the concordance coefficients for the selected level.

6. If $W_R < W_T$, i.e. when the opinions of experts do not coincide, they have the opportunity to get acquainted with the answers of other experts, to analyze and correct their previous assessments, i.e. the expert procedure is repeated.

7. The obtained information is processed by the methods of the theory of fuzzy sets, the process of defuzzification is carried out and specific values of the coefficients of the models are determined. Defuzzification allows to find a «typical representative» of a fuzzy set, given by its own membership function. Any defuzzification method (DFM) can be viewed as a mapping DFM: $[0,1]^R \rightarrow R$, where R – the set of real numbers, $[0,1]^R$ – set of functions defined on R and taking values on the interval [0,1]. Various defuzzification methods are known, for example, the centroid method, the first (left) maximum method, the last (right) maximum method, and the average

maximum method. It is recommended to use the more well-known and convenient of them, the average maximum method. Explanation of this method: let M be the largest value of the combined membership function MY on the domain $D(Y)$. The numerical value of the output variable Y is defined as the arithmetic mean of those numbers $x \in D(Y)$, for which $M^Y(x)=M$.

To increase the reliability of the obtained expert data, it is proposed to carry out an additional examination, incl. «Anti-expertise» [102]. When carrying out «anti-examination», expert survey cards are made up of questions that are opposite in meaning to those for which answers have already been received and membership functions have been built – $\mu_{\tilde{A}}(x)$. At the same time, experts should assess the degree of non-belonging of fuzzy parameters to subsets that vaguely describe the functioning of the object. Based on the results of processing the obtained ones, the functions of non-belonging of the fuzzy parameters of the object to the original term-sets are built.

A qualitative analysis of the degree of consistency of estimates can be carried out by the values of the membership function and non-membership function. For this, the difference between the values of these functions, which describe the same parameter at some points, is compared. Of interest are those points at which the values of the membership function and non-membership function differ significantly. If there are such intervals, then additional research should be carried out together with experts, to identify the reasons for the discrepancy between the estimates and make the necessary adjustments to the estimates.

2.6 EXPERT ASSESSMENT FOR THE MATHEMATICAL DESCRIPTION OF THE TECHNOLOGICAL COMPLEX OF THE REFORMING UNIT, DEVELOPMENT OF A METHOD FOR CONDUCTING EXPERT PROCEDURES IN A FUZZY ENVIRONMENT

When developing mathematical models of technological objects of oil refining production, problems of a shortage of reliable statistical information often arise. It may not be possible or economically feasible to conduct proactive experiments to collect the necessary quantitative information. Under these conditions, undoubtedly, to collect the missing part of the necessary information, one should rely on the experience, knowledge and intuition of experienced production personnel, specialists, i.e. it is necessary to organize and conduct peer reviews. Thus, the methods of expert assessments are methods of organizing work with expert specialists and processing expert opinions expressed in quantitative and/or qualitative form in order to develop a mathematical description and models of the object under study or to prepare information for decision making by decision makers.

To carry out work using the method of expert assessments, a Working Group (WG) is created, which organizes, on behalf of the decision maker, the activities of experts united (formally or essentially) in an expert commission (EC). There are many methods for obtaining expert judgment. In some, they work with each expert separately, it does not even know who else is an expert, and therefore expresses its opinion regardless of the authorities. In others, experts are brought together to prepare materials for decision makers, while experts discuss the problem with each other, learn from each other, and discard wrong opinions. In some methods, the number of experts is fixed and such that statistical methods of checking the consistency of opinions and then averaging them allow to make informed decisions. In others, the number of experts grows during the examination process, for example, when using the «snowball» method. Currently, there is no scientifically substantiated classification of methods of expert assessments, and even more so – unambiguous recommendations for their application [56].

Let's consider the main results of organizing and conducting expert assessments in order to collect the necessary information for the development of mathematical models of technological objects of oil refining on the example of units of the catalytic reforming unit of the LG-35-11/300-95 unit of the Atyrau refinery. The primary goal of organizing and conducting an expert assessment was to find out and select the most significant input, operating and output parameters of the object, taking into account their degree of importance (weights).

As already noted, the catalytic reforming unit is designed to convert naphthenes and paraffins into aromatic hydrocarbons, which are then used as commercial gasoline as part of the process product, platformate (due to high octane numbers).

The expert survey was carried out among the experts serving the unit. Their role was played by the unit process engineer, three senior operators, two instrumentation and control specialists, the head of the LG unit and the head of the shop. A total of 8 experts participated in the survey.

The survey consisted of two stages. At the first stage, the experts had to determine and rank the main input parameters of the unit. The ranks were represented as a series of numbers from 1 to 10. At the second stage, it was necessary to assess the influence of the input parameters ranked at the first stage on the output parameters: on the quantity and quality of the products produced.

When performing the first stage of the survey, it was assumed that the most important parameter will occupy 1 (first) rank, the second most important parameter will be 2 (second) rank, etc. Moreover, it was indicated that if, according to the expert, some parameter does not affect the process or its influence can be neglected, the expert should exclude it from the list, and also, if among the parameters proposed in the list there were no input, mode parameters that, in the opinion of experts influence the process, they could additionally include this parameter in the list on their own.

If there are no input parameters having the same ranks (having the same effect on the output), then the number of ranks and input parameters are the same. If some parameters have the same effect on the output parameter, they can have the same rank.

Expert survey map. The expert survey consists of two stages. At the first stage, it is necessary *to determine and rank* the main input parameters. At the second stage, it is necessary *to assess the influence* of the input parameters ranked at the first stage on the output parameters (quality indicators of the manufactured products of the LG-35-11/300-95 unit of shop No. 3).

The purpose of this survey is *to determine* the main input parameters that affect the process, the output parameters of the LG-35-11/300-95 unit of shop No. 3.

At the second stage of the survey, the influence of the input parameters (selected input parameters at the first stage of the survey) on the output parameters is assessed.

The experts were offered a list of input, operating parameters of the main units of the LPG unit of the Atyrau refinery, i.e. hydrotreating unit, reforming unit, stabilization units and furnaces to assess their impact on the process. The results of adjusting the proposed list from the questionnaires, i.e. deletions and additions of parameters and the results of the assessment in the form of ranks are shown below in **Tables 2.2–2.5**.

Table 2.2 List of input, operating parameters of the hydrotreating unit of the LG-35-11/300-95 unit and the results of the expert evaluation

Parameters	Input parameters	Rank
Loading of raw materials on H/T, m^3/h	66 m^3/h	1
Pressure from CB-1, 1a, kg/m^2	42 kg/cm^2	8
After T-2	100 °C	4
Bottom K-1	190 °C	3
In T-3	185 °C	4
Top K-1	100 °C	4
After T-20	150 °C	5
After RC-1	35 °C	6
After R-1	52 °C	5
Pressure in K-1, kg/cm^2	12.0 kg/cm^2	7
Pressure in S-2, kg/cm^2	10.0 kg/cm^2	7
Gas consumption from K-3 Pumping from S-2 to K-6	1040 m^3/h	9
Pumping from S-2 to K-6	9.0 m^3/h	10
Irrigation consumption in K-1	4.0 m^3/h	8
Loading K-1	68 m^3/h	2
Inlet pressure PC-1.2, kg/cm^2	27.0 kg/cm^2	4
Discharge pressure PC-1.2, kg/cm^2	36.0 kg/см^2	4
HCG temperature at the PC reception – 1.2, °C	59 °C	3
HCG temperature at the PC outlet – 1.2, °C	88 °C	3
HCG consumption from PC-1.2 for H/T, m^3/h	16500 m^3/h	2
Consumption of HCG with H/T in fuel network, m^3/h	8000 m^3/h	6
Pressure, kg/cm^2 In S-4	27.0 kg/cm^2	5
Instrumentation air	2.6 kg/cm^2	0
Fuel gas	3.5 kg/cm^2	0
Liquid fuel	7.0 kg/cm^2	0
Steam 10 atm.	7.0 kg/cm^2	0

Table 2.3 List of input, operating parameters of the reforming unit of the LG-35-11/300-95 unit and the results of the expert assessment

Parameters	**Input parameters**	**Rank**
Loading, m^3/h	62 m^3/h	2
Discharge pressure CB-2.3, kg/cm^2	44 kg/cm^2	
Consumption, m^3/h HCG to the reforming system	92000 m^3/h	2
WASH from reforming to H/T	14500 m^3/h	7
DCE solution for reception CB-2.3	1.6	6
DCE solution concentration	32/100 l	6
Amperage CV-1, A	245	3
Temperature, °C After T-6/4, T-6a/4	435 °C	3
Entrance to R-2	486 °C	1
Exit from R-2	425 °C	1
Entrance to R-3	486 °C	1
Exit from R-3	464 °C	1
Entrance to R-4, 4a	486 °C	1
Exit from R-4, 4a	482 °C	1
Before ACRC 106, 106a	120 °C	5
After ACRC-106, 106a	100 °C	4
After RC-6, 6a	64 °C	4
GB-1	168 °C	10
AB-1	145 °C	10
Pressure, kg/cm^2 In R-2	27 kg/cm^2	9
In R-3	25 kg/cm^2	9
In R-4, 4a	23 kg/cm^2	9
S-9	22 kg/cm^2	8
CV-1 receprtion	19.5 kg/cm^2	8
CV-1 discharge	31.5 kg/cm^2	8
Axial shear oils	1.63 kg/cm^2	1

Table 2.4 List of input, operating parameters of the stabilization unit of the LG-35-11/300-95 unit and the results of the expert assessment

Parameters	Input parameters	Rank
Furnace F-2 Pressure in S-8, kg/cm^2	15 kg/cm^2	6
Heat amplifier	36 °C	1
Flue gas temperature at the pass, °C	210 °C	7
Product outlet temperature, °C	135 °C	1
Furnace P-3 Heating agent consumption	44 °C	1
Flue gas temperature at the pass, °C	415 °C	7
Product outlet temperature, °C	195 °C	1
Irrigation 34 plate		
40 plate		
46 plate		
K-6 Temperature after T-7-x, °C	120 °C	3
Bottom temperature K-6, °C	120 °C	2
Temperature on 34 plate, °C	24 °C	4
Temperature on 40 plate, °C	20 °C	4
Temperature on 46 plate, °C	19 °C	4
Top temperature, °C	18 °C	2
Pressure, kg/cm^2	10.0 kg/cm^2	5
K-7 Temperature after T-8/2, °C	144 °C	3
Bottom temperature, °C	165 °C	2
Top temperature, °C	50 °C	2
Pressure, kg/cm^2	11 kg/cm^2	5
Irrigation	10	4
Temperature after RC-12, °C	28 °C	6
Pressure in E-7, kg/cm^2	10.8 kg/cm^2	5
Temperature after R-13, °C	42 °C	7

Table 2.5 List of input, operating parameters of the block of furnaces of the LG-35-11/300-95 unit and the results of expert assessment

Parameters	Input parameters	Rank
Hydrotreating furnace F-101 Temperature, °C On the passes G-8		4
Mixture product G-9	325 °C	1
Mixture product G-10	325 °C	1
At the exit G-11	325 °C	2
Gasoline in the furnace p. 3a	185 °C	1
Gasoline in the furnace p. 3b	173 °C	1
At the exit from convection-4a	208 °C	3
Pos. 4b	209 °C	3
Pos. 5a	214 °C	3
Pos. 5b	210 °C	3
Pressure in the line G-24, kg/cm^2	30 kg/cm^2	4
Pressure in the line G-25, kg/cm^2	30 kg/cm^2	4
Reforming furnace P-1 Temperature, °C At the entrance to the convention	435 °C	2
At the exit from convection	466 °C	3
Flue gases in convection	702 °C	4
Flue gas in 1 chamber	795 °C	4
Flue gas in 2 chamber	695 °C	4
Flue gas in 3 chamber	735 °C	4
Flue gas in 4 chamber	740 °C	4
Flue gas in 5 chamber	805 °C	4
Flue gas in the riser	439 °C	4
R-2 *Temperature*, °C Pos. 851	486 °C	1
Pos. 852	486 °C	1
Pos. 853	488 °C	1
Pos. 854	490 °C	1
R-3 *Temperature*, °C Pos. 856	488 °C	1
Pos. 857	485 °C	1
R-4,4a *Temperature*, °C Pos. 846	485 °C	1
Pos. 847	472 °C	1

As it is possible to see from the results of the survey, the experts ranked the selected parameters in points from 1 to 10, and when assessing the results, they mainly used only a few numbers from the interval from 1 to 6. The rest of the numbers were used extremely rarely for the assessment. Therefore, a survey using a numerical scale did not give us a complete and adequate picture of assessing the impact of input parameters on weekends. During the assessment, certain difficulties arose with the representation of the significance of the influence of one or another parameter on the parameters of the final product, the degree of superiority of one of the parameters over others.

Thus, according to the results of expert assessment and research, it was revealed that the main input, operating parameters that more strongly affect the catalytic reforming process include: the volume and rate of raw material loading, the temperature at the inlet and outlet of reactors R-2, R-3, R-4, 4a, pressure in these reactors, temperature in the furnace F-1, hydrogen/raw material ratio and raw material properties.

Similarly, questionnaires were drawn up for experts in order to assess and select the main output parameters of the catalytic reforming process. Expert assessments have been carried out. As a result of processing the data of the expert assessment and on the basis of other studies carried out, the following were selected as the main output parameters of the process: the volume of production-catalyzate (debutanized gasoline); the volume of dry gas, hydrogen-containing gas, as well as the quality indicators of gasoline: octane number according to the motor method; fractional composition; vapor pressure, actual resin content, water-soluble acid and alkali content.

It is believed that a decision can be made only on the basis of the agreed opinions of experts. Therefore, those whose opinion differs from the opinion of the majority are excluded from the expert group. At the same time, both unqualified persons who were included in the expert commission due to a misunderstanding or for reasons unrelated to their professional level are eliminated, as well as the most original thinkers who have penetrated deeper into the problem than most.

Since the number of experts usually does not exceed a certain number (15–20), the formal statistical consistency of experts' opinions can be combined with the actually existing division into groups, which makes further calculations irrelevant to reality. If to turn to specific calculation methods, for example, using the concordance coefficients based on the Kendall or Spearman rank correlation coefficients [57], then it must be remembered that in fact a positive result of checking the consistency in this way means nothing more or less than the rejection of the hypothesis on the independence and uniform distribution of expert opinions on the set of all rankings.

At the second stage, the experts were asked to assess the influence of the input and operating parameters selected at the first stage on the selected output parameters, on the quantity and quality of the catalyzate.

Certain problems arose during this stage of the examination. The experts could indicate which input parameters influence which output parameters, but they found it difficult to clearly assess on a point scale how they influence and determine the comparative weights of their effects. Each object can be assessed according to many quality indicators. The question arises, is it possible to bring the estimates for these indicators together? Thus, a specific (narrow) formulation of the problem for experts is important. But there is often no such setting. And then the «games» for the development of a generalized quality indicator do not have an objective character. An alternative to the only generalized indicator is a mathematical apparatus such as multicriteria optimization – Pareto sets, etc.

In some cases, it is still possible to globally compare objects – for example, with the help of the same experts, it is possible to get the ordering of the objects under consideration – the process parameters. Then it is possible to choose the coefficients for the individual indicators so that the ordering using a linear function corresponds as closely as possible to the global ordering. On the contrary, in such cases, it is not possible to assess the indicated coefficients with the help of experts.

This simple idea has not yet become obvious to individual compilers of methods for conducting expert surveys and analyzing their results. They try hard to get the experts to do what they cannot do-indicate the weights with which individual quality indicators should be included in the final aggregate indicator. Experts can usually compare objects or projects in general, but cannot isolate the contribution of individual factors. Once the organizers of the survey ask, the experts answer, but these answers do not carry reliable information about reality.

These problems in expert assessment push to other ways of solving the problem, for example, to conduct an examination in a convenient natural or professional language of experts (fuzzy examination), then formalize and process the assessment results using theories of fuzzy sets and possibilities, which is a new and promising direction. methods of expert assessment.

In this direction, in this work, a method for conducting expert procedures in a fuzzy environment has been developed. The apparatus for formalizing and processing qualitative information is the methods of fuzzy mathematics, the theory of possibilities [107, 108].

With the competence of experts and with the correct organization of their survey, collection and processing of high-quality information on its basis, it is possible to build models that take into account all the complex relationships of various parameters and variables of a production facility. The resulting models can be more meaningful than the models developed by traditional methods, and most importantly, adequately describe real production facilities and tasks. Effective formalization of qualitative information, which is knowledge, judgments of expert experts about the object under study, can be carried out on the basis of the methods of the theory of fuzzy sets and possibilities [58, 59, 106–108].

In the proposed new method of expert assessment, which allows organizing and conducting an expert survey in a fuzzy environment, experts assess and describe the influence of input parameters on outputs verbally (qualitatively) based on their knowledge and experience, using the methodology of the theory of fuzzy sets and possibilities. The results obtained are also processed by the methods of the theory of fuzzy sets and possibilities, and then used in the development of mathematical models of the object under study.

At the first stage of solving the problem, an expert assessment is organized and conducted based on the well-known Delphi method. After analyzing the results of ranking the input parameters of the process and processing the results of the survey, the following input, operating parameters of technological units of the catalytic reforming unit of the unit are identified, which most strongly affect the process: the volume and speed of loading of raw materials; temperature at the inlet and outlet of reactors R-2, R-3, R-4, 4a; pressure in R-2, R-3, R-4, 4a; temperature in the F-1 furnace; hydrogen/raw materials ratio and raw material properties.

At the second stage of solving the problem within the framework of the work, an expert survey was conducted to determine the degree of influence of the input, operating parameters of the reforming unit on the output parameters of the process, i.e. on the quality and quantity of target products. The target products of this unit are high-octane gasoline (catalyzate), dry and hydrogen-containing gases. The monitored and controlled parameters also include the quality indicators of gasoline: octane number; fractional composition (distillation 10 % and 50 %); saturated steam pressure; actual resin content; the content of water-soluble acids and alkalis.

When performing this stage of the examination, as already noted, certain problems arose due to the fact that experts, although they could indicate which input parameters affect which output parameters, but found it difficult to clearly assess the degree of influence on a point scale and determine the comparative weights of their effects. Difficulties arose with the representation of the significance of the influence of one or another input parameter on the parameters of the final product, the degree of superiority of one of the parameters over others, and it was not possible to assess whether the *i*-th parameter would be superior in significance to other parameters.

It should be noted that they could assess these influences of the input parameters on the output in fuzzy terms, such as strong, very strong, weak, approximately equivalent, etc., but the known methods of expert assessments do not allow processing such information of a fuzzy nature.

Why is it difficult for experts to rank parameters using numbers? What is the reason for this? The most common answer is that people don't think in numbers. In human thinking, images, words, but not numbers are used. Therefore, demanding an answer from an expert in the form of a number means putting it in a dead-end situation.

An expert can compare various parameters of an object, alternatives, etc., give them verbal assessments of «significant», «acceptable», «less significant compared to…», «strongly affects…», «weakly affects», arrange several objects by attractiveness, but usually cannot say by how many times or by how many times one parameter or alternative is superior in importance to another. In other words, the expert's answers are usually measured on an ordinal scale, they are rankings, the results of pairwise comparisons, and other objects of a non-numerical nature. Most often, experts try to consider the answers of experts as numbers, they are engaged in «digitizing» their opinions, assigning numerical values to these opinions – points, which are then processed using the methods of applied statistics as the results of ordinary physical measurements. In the case of arbitrary digitization, the conclusions obtained as a result of data processing may not correspond to reality.

Therefore, one of the solutions to this problem is the use of high-quality expert assessments, i.e. expert judgment in a fuzzy environment containing no numbers. They can be divided into two groups:

– estimates carried out according to pre-compiled scales (assessment of qualitative characteristics);

– estimates for which scales cannot be compiled in advance.

The estimates of the first group are used to determine the values of characteristics that have a qualitative variation, all the values of which can be listed in advance and defined by some standard terms or expressions. For example, the sign «the influence of the input process parameter on the quantity and quality of the final product» can have the following gradations: the product yield increases greatly, and the product quality deteriorates; the quantity of the product increases, the quality does not change; the quantity of the product received does not change, the quality improves, etc.

Assessing the influence of this parameter on the quantity and quality, the expert points to one of the listed gradations and, therefore, selects an assessment from a number of predetermined values.

The estimates of the second group, which do not have pre-compiled scales, are used in generating operations. They are expressed in proposals, hypotheses, lists of certain indicators, facts. Qualitative expert assessment in the form of lists of future events or chains of interrelated events appears when solving forecasting problems and drawing up scenarios. Expert evaluations in the fuzzy environment of this group, which have the character of recommendations for choosing a particular sequence of actions, are found in the tasks of managing technological objects.

Due to the complexity of technological processes and oil refining facilities, the lack or absence of industrial measuring and control instruments, the presence of a human operator in the control process, the information collected about their functioning is usually fuzzy. Under these conditions, to assess fuzzy parameters, it is necessary to carry out an expert procedure in a fuzzy environment. Creation of procedures for assessing data and choosing decisions in the presence of fuzzy factors is based on the use of expert opinions and the theory of fuzzy sets. Let's consider the main steps of the algorithm for expert assessment in a fuzzy environment (EE in FE), i.e. expert judgment based on quality information.

EE algorithm in FE:

1. Categorization of the object of assessment, classes of tasks and operations.
2. Choice of a class of qualifiers (linguistic variables, term-set), adequate to the object of assessment and the class of operations.
3. Choice of the type of scales that describe the object and tasks.
4. Determination of the assessment method and the conduct of the assessment.
5. Based on the analysis of the object under study, a complete plan of «mental» experiments is drawn up. Drawing up a plan is similar to drawing up a plan for mathematical planning of experiments, where instead of quantitative data, their approximate values in the form of fuzzy numbers or the value of a linguistic variable in the form of fuzzy information (term) are used.
6. Experts, on the basis of practical experience and knowledge, cut off plan options that are practically unrealizable or clearly lead to emergency situations (while they must justify the reasons for excluding each option from the plan).
7. For all other options, the experts qualitatively assess the influence of this ratio of input factors on the output parameters of the object (experience options). The assessment is carried out on the basis of term sets, which are selected in paragraph 2.
8. In case of uncertainty of experts in assessing some options, it is necessary to implement these options as possible in accordance with the plan and assess the results.
9. Checking for subjective compatibility of features and their totality (compliance with the intuitive image of the object). Since a group of experts should participate in assessing plans, the

next step is to determine the degree of agreement between their opinions using a well-known method. If the opinions of the experts mostly coincide, i.e. the values of the dispersion coefficient of concordance are close to 1 and $W_R \geq W_T$, then the implementation of plans and the transition to the processing of the results obtained, where W_R, W_T are the calculated and tabular values of the coefficients of concordance for the selected level, respectively.

10. If $W_R < W_T$, i.e. when the opinions of experts do not coincide, they have the opportunity to get acquainted with the answers of other experts, to analyze and correct their previous assessments, i.e. the expert procedure is repeated.

11. To obtain the final results, the information obtained is processed by the methods of the theory of fuzzy sets and possibilities.

This algorithm is based on a combination of the following main factors: the characteristics of the problem, the class of fuzzy categories, the method of forming the scales, the method of polling experts and processing the obtained qualitative information.

In specific tasks, the following ways of representing fuzzy parameters are considered: by the value of the membership function $\mu_c(x) \in [0,1]$; value on a scale that is a collection of fixed elements x_q; as an analytical function. It is convenient to represent fuzzy parameters in parametric form as a triangle, trapezoid, or exponential curve. These methods of representing fuzzy parameters are also suitable for obtaining relative fuzzy measures.

Table 2.6 presents a fragment of the questionnaire for a fuzzy expert assessment of the influence of the input parameters of the catalytic reforming unit on the quantity and quality of target products (output parameters) and the results of the assessment. Fuzzy numbers and sets describing the accepted term-sets and membership functions describing them are shown in **Table 2.7**.

Table 2.6 Assessment of the influence of the input, operating parameters of the reforming unit of the LG unit on the output parameters

No.	Input, mode parameters										Output parameters							
	x_1 – volume of loading of raw material	x_2 – volumetric velocity in reactors	x_3^{R2} – temperature in reactor R-2	x_3^{R3} – temperature in reactor R-3	$x_3^{R4,\,4a}$ – temperature in reactors R-4, 4a	x_4^{R2} – pressure in reactor R-2	x_4^{R3} – pressure in reactor R-3	$x_4^{R4,\,4a}$ – pressure in reactors R-4, 4a	x_5 – H_2/raw materials ratio	x_6 – temperature in furnace F-1	$y_1^{R_j}$ – volume of catalyzate from the reactor j	y_2 – dry gas volume	y_3 – HCG volume	y_4 – octane number of gasoline	y_5 – fractional composition 10 % dist.	y_6 – fractional composition 50 % dist.	y_7 – saturated vapor pressure	y_8 – content of actual resins
1	n	n	n	n	n	n	n	n	n	n	av	av	aa	n	n	n	n	bn
2	an	n	n	n	n	n	n	n	n	n	aa	a	av	n	n	n	bn	n

Designations: n – norm; av – average; aa – above average; bn – below normal; an – above normal; etc.

Table 2.7 Membership functions of linguistic variables describing the operation of the reforming unit of the LG unit of the Atyrau refinery

Parameters, linguistic variables	Term set	Change interval	Membership functions
1	**2**	**3**	**4**
Input parameters			
Volume of loading of raw material – x_1, m^3/h	below normal	55–65	$\mu_{A_1^1} = \exp\left(Q_1^1 C_1^1 \left\|(x_1 - 60)^{N_{A_1^1}}\right\|\right)$
	norm	60–75	$\mu_{A_1^2} = \exp\left(Q_1^2 C_1^2 \left\|(x_1 - 67)^{N_{A_1^2}}\right\|\right)$
	above normal	70–80	$\mu_{A_1^3} = \exp\left(Q_1^3 C_1^3 \left\|(x_1 - 75)^{N_{A_1^3}}\right\|\right)$
Volumetric velocity in reactors – x_2, h^{-1}	low	1.0–1.2	$\mu_{A_2^1} = \exp\left(Q_2^1 C_2^1 \left\|(x_2 - 1.10)^{N_{A_2^1}}\right\|\right)$
	average	1.1–1.4	$\mu_{A_2^2} = \exp\left(Q_2^2 C_2^2 \left\|(x_2 - 1.25)^{N_{A_2^2}}\right\|\right)$
	high	1.3–1.5	$\mu_{A_2^3} = \exp\left(Q_2^3 C_2^3 \left\|(x_2 - 1.40)^{N_{A_2^3}}\right\|\right)$
Temperature in reactor R-2 – x_3^{R2}, °C	low	470–485	$\mu_{A_3^1} = \exp\left(Q_3^1 C_3^1 \left\|(x_3^{R_2} - 477)^{N_{A_3^1}}\right\|\right)$
	average	485–495	$\mu_{A_3^2} = \exp\left(Q_3^2 C_3^2 \left\|(x_3^{R_2} - 490)^{N_{A_3^2}}\right\|\right)$
	high	495–510	$\mu_{A_3^3} = \exp\left(Q_3^3 C_3^3 \left\|(x_3^{R_2} - 500)^{N_{A_3^3}}\right\|\right)$
Temperature in reactor R-3 – x_3^{R3}, °C	low	480–495	$\mu_{A_3^1} = \exp\left(Q_3^1 C_3^1 \left\|(x_3^{R_3} - 487)^{N_{A_3^1}}\right\|\right)$
	average	495–505	$\mu_{A_3^2} = \exp\left(Q_3^2 C_3^2 \left\|(x_3^{R_3} - 500)^{N_{A_3^2}}\right\|\right)$
	high	505–520	$\mu_{A_3^3} = \exp\left(Q_3^3 C_3^3 \left\|(x_3^{R_3} - 512)^{N_{A_3^3}}\right\|\right)$
Temperature in reactors R-4, 4a – x_3^{R3}, °C	low	490–498	$\mu_{A_3^1} = \exp\left(Q_3^1 C_3^1 \left\|(x_3^{R_{4,4a}} - 494)^{N_{A_3^1}}\right\|\right)$
	average	498–518	$\mu_{A_3^2} = \exp\left(Q_3^2 C_3^2 \left\|(x_3^{R_{4,4a}} - 503)^{N_{A_3^2}}\right\|\right)$
	high	518–525	$\mu_{A_3^3} = \exp\left(Q_3^3 C_3^3 \left\|(x_3^{R_{4,4a}} - 521)^{N_{A_3^3}}\right\|\right)$
Pressure in reactor R-2 – x_4^{R2}, kg/cm^2	low	25–30	$\mu_{A_4^1} = \exp\left(Q_4^1 C_4^1 \left\|(x_4^{R_2} - 27)^{N_{A_4^1}}\right\|\right)$
	average	28–38	$\mu_{A_4^2} = \exp\left(Q_4^2 C_4^2 \left\|(x_4^{R_2} - 33)^{N_{A_4^2}}\right\|\right)$
	high	34–39	$\mu_{A_4^3} = \exp\left(Q_4^3 C_4^3 \left\|(x_4^{R_2} - 36)^{N_{A_4^3}}\right\|\right)$

Continuation of Table 2.7

1	2	3	4
Pressure in reactor R-3 – x_4^{R3}, kg/cm²	low	22–27	$\mu_{A_4^1} = \exp\left(Q_4^1 C_4^1 \left\|\left(x_4^{R_3} - 25\right)^{N_{A_4^1}}\right\|\right)$
	average	25–32	$\mu_{A_4^2} = \exp\left(Q_4^2 C_4^2 \left\|\left(x_4^{R_3} - 29\right)^{N_{A_4^2}}\right\|\right)$
	high	30–35	$\mu_{A_4^3} = \exp\left(Q_4^3 C_4^3 \left\|\left(x_4^{R_3} - 33\right)^{N_{A_4^3}}\right\|\right)$
Pressure in reactors R-4, 4a – $x_4^{R4,\,4a}$, kg/cm²	low	20–24	$\mu_{A_4^1} = \exp\left(Q_4^1 C_4^1 \left\|\left(x_4^{R_{4,4a}} - 22\right)^{N_{A_4^1}}\right\|\right)$
	average	23–27	$\mu_{A_4^2} = \exp\left(Q_4^2 C_4^2 \left\|\left(x_4^{R_{4,4a}} - 25\right)^{N_{A_4^2}}\right\|\right)$
	high	26–30	$\mu_{A_4^3} = \exp\left(Q_4^3 C_4^3 \left\|\left(x_4^{R_{4,4a}} - 28\right)^{N_{A_4^3}}\right\|\right)$
H_2/raw material ratio – x_5, nm³	below normal	300–350	$\mu_{A_5^1} = \exp\left(Q_5^1 C_5^1 \left\|\left(x_5 - 325\right)^{N_{A_5^1}}\right\|\right)$
	norm	350–450	$\mu_{A_5^2} = \exp\left(Q_5^2 C_5^2 \left\|\left(x_5 - 400\right)^{N_{A_5^2}}\right\|\right)$
	above normal	450–500	$\mu_{A_5^3} = \exp\left(Q_5^3 C_5^3 \left\|\left(x_5 - 425\right)^{N_{A_5^3}}\right\|\right)$
Temperature in furnace F-1 – x_6, °C	low	500–510	$\mu_{A_6^1} = \exp\left(Q_6^1 C_6^1 \left\|\left(x_6 - 505\right)^{N_{A_6^1}}\right\|\right)$
	average	510–520	$\mu_{A_6^2} = \exp\left(Q_6^2 C_6^2 \left\|\left(x_6 - 515\right)^{N_{A_6^2}}\right\|\right)$
	high	520–530	$\mu_{A_6^3} = \exp\left(Q_6^3 C_6^3 \left\|\left(x_6 - 525\right)^{N_{A_6^3}}\right\|\right)$
Output parameters			
Catalyzate volume – y_1, m³/h	few	54–64	$\mu_{B_1^1} = \exp\left(Q_1^1 C_1^1 \left\|\left(y_1 - 59\right)^{N_{B_1^1}}\right\|\right)$
	average	62–72	$\mu_{B_1^2} = \exp\left(Q_1^2 C_1^2 \left\|\left(y_1 - 67\right)^{N_{B_1^2}}\right\|\right)$
	a lot of	69–79	$\mu_{B_1^3} = \exp\left(Q_1^3 C_1^3 \left\|\left(y_1 - 74\right)^{N_{B_1^3}}\right\|\right)$
Dry gas volume – y_2, m³/h	few	919–924	$\mu_{B_2^1} = \exp\left(Q_2^1 C_2^1 \left\|\left(y_2 - 922\right)^{N_{B_2^1}}\right\|\right)$
	average	922–927	$\mu_{B_2^2} = \exp\left(Q_2^2 C_2^2 \left\|\left(y_2 - 925\right)^{N_{B_2^2}}\right\|\right)$
	a lot of	925–930	$\mu_{B_2^3} = \exp\left(Q_2^3 C_2^3 \left\|\left(y_2 - 928\right)^{N_{B_2^3}}\right\|\right)$
HCG volume – y_3, m³/h	few	99400–99900	$\mu_{B_3^1} = \exp\left(Q_3^1 C_3^1 \left\|\left(y_3 - 99650\right)^{N_{B_3^1}}\right\|\right)$
	average	99800–100300	$\mu_{B_3^2} = \exp\left(Q_3^2 C_3^2 \left\|\left(y_3 - 100050\right)^{N_{B_3^2}}\right\|\right)$
	a lot of	100000–100500	$\mu_{B_3^3} = \exp\left(Q_3^3 C_3^3 \left\|\left(y_3 - 100250\right)^{N_{B_3^3}}\right\|\right)$

Continuation of Table 2.7

1	2	3	4
Octane number of gasoline – y_4 (by motor method)	low	84–86	$\mu_{B_4^1} = \exp\left(Q_4^1 C_4^1 \left\|(y_4 - 85)^{N_{B_4^1}}\right\|\right)$
	average	86–88	$\mu_{B_4^2} = \exp\left(Q_4^2 C_4^2 \left\|(y_4 - 87)^{N_{B_4^2}}\right\|\right)$
	high	87–90	$\mu_{B_4^3} = \exp\left(Q_4^3 C_4^3 \left\|(y_4 - 88)^{N_{B_4^3}}\right\|\right)$
Fractional composition of catalyst 10 % distillation – y_5, °C	below normal	54–64	$\mu_{B_5^1} = \exp\left(Q_5^1 C_5^1 \left\|(y_5 - 59)^{N_{B_5^1}}\right\|\right)$
	norm	62–72	$\mu_{B_5^2} = \exp\left(Q_5^2 C_5^2 \left\|(y_5 - 67)^{N_{B_5^2}}\right\|\right)$
	above normal	69–79	$\mu_{B_5^3} = \exp\left(Q_5^3 C_5^3 \left\|(y_5 - 74)^{N_{B_5^3}}\right\|\right)$
Fractional composition of catalyst 50 % distillation – y_6, °C	below normal	105–115	$\mu_{B_6^1} = \exp\left(Q_6^1 C_6^1 \left\|(y_6 - 110)^{N_{B_6^1}}\right\|\right)$
	norm	113–117	$\mu_{B_6^2} = \exp\left(Q_6^2 C_6^2 \left\|(y_6 - 115)^{N_{B_6^2}}\right\|\right)$
	above normal	116–126	$\mu_{B_6^3} = \exp\left(Q_6^3 C_6^3 \left\|(y_6 - 120)^{N_{B_6^3}}\right\|\right)$
Saturated vapor pressure – y_7, mm Hg	low	490–497	$\mu_{B_7^1} = \exp\left(Q_7^1 C_7^1 \left\|(y_7 - 493)^{N_{B_7^1}}\right\|\right)$
	average	495–505	$\mu_{B_7^2} = \exp\left(Q_7^2 C_7^2 \left\|(y_7 - 500)^{N_{B_7^2}}\right\|\right)$
	high	503–510	$\mu_{B_7^3} = \exp\left(Q_7^3 C_7^3 \left\|(y_7 - 507)^{N_{B_7^3}}\right\|\right)$
Content of actual resins for 100 ml of gasoline – y_8, mg	few	3–5	$\mu_{B_8^1} = \exp\left(Q_8^1 C_8^1 \left\|(y_8 - 4)^{N_{B_8^1}}\right\|\right)$
	average	4–6	$\mu_{B_8^2} = \exp\left(Q_8^2 C_8^2 \left\|(y_8 - 5)^{N_{B_8^2}}\right\|\right)$
	a lot of	6–8	$\mu_{B_8^3} = \exp\left(Q_8^3 C_8^3 \left\|(y_8 - 7)^{N_{B_8^3}}\right\|\right)$

Let's note that the formal presentation of fuzzy characteristics can be carried out in the following main ways: direct dialogue between the researcher (consultant) and the decision maker (expert); dialogue between the decision maker and the computer; dialogue between decision makers and partners in communication with the help of computers.

The listed ways of representing fuzzy parameters are used depending on the type and nature of the specific problem being solved. The latter way is more effectively applied in a wide range of communication tasks arising in organizational systems in which the decision maker is in a complex system of relationships with independent objects that have their own criteria and limitations.

2.7 BUILDING OF A SYSTEM OF MATHEMATICAL MODELS OF THE MAIN UNITS OF THE HYDROTREATING UNIT BASED ON STATISTICAL AND FUZZY INFORMATION

This paragraph presents the results of the development of mathematical models of the hydrotreating reactor, stripping column, absorbers and hydrotreating furnace, which are the main units of the hydrotreating unit of the catalytic reforming unit. Since these objects of modelling the reforming unit of the Atyrau oil refinery operate in conditions of a deficit and indistinctness of initial information, their mathematical models are developed on the basis of a systematic approach, using available information of a different nature (experimental statistical data, fuzzy information from experts) with the use of appropriate building methods. mathematical models.

Mathematical models describing the dependence of the yield of products from the hydrotreating reactor, columns and furnaces are developed in the form of nonlinear regression models based on experimental and statistical data. And the models that assess the quality indicators of the products produced from the hydrotreating reactor and columns, i.e. hydrogenate, hydrogen-containing and hydrocarbon-containing gases are built on the basis of fuzzy information from experts in the form of fuzzy multiple regression equations. A graph of the dependence of the hydrogenated product yield on the temperature in the hydrotreating reactor is plotted. To describe the dependence of the optimal temperature of the hydrotreating process on the quality of raw materials, a linguistic model has been built on the basis of linguistic rules of conditional inference and fuzzy information. Membership functions of fuzzy parameters are built for the linguistic model.

The hydrotreating unit of the catalytic reforming unit is one of the main units of this unit. In the hydrotreating unit, the process of hydrotreating of straight-run gasoline from the primary oil refining unit takes place. At the same time, the quality of oil products is improved due to the removal of sulfurous, as well as other harmful compounds and impurities from their composition, which worsen the operational characteristics of technological equipment and metal aggregates. Thus, the hydrotreating process can reduce corrosion of metal equipment and pollution of the environment and atmosphere. Therefore, the study and improvement of oil refining hydrotreating processes based on scientifically grounded methods, for example, methods of mathematical modelling and optimization, is an urgent task of technological science and oil refining production.

Let's consider the description of the process flow diagram of the hydrotreating unit of the catalytic reforming unit of the Atyrau refinery shown in **Fig. 2.4**. The catalytic reforming process is intended for the production of high-octane motor gasoline, raw material for petrochemical synthesis (aromatic hydrocarbons) and hydrogen-containing gas (HCG), which is used in the hydrogenation processes of oil refining. The target products of the LG-35-11/300-95 catalytic reforming unit at the Atyrau Refinery include high-octane commercial gasoline and liquefied domestic gas.

The LG unit consists of 4 blocks: a block for preliminary hydrotreating of raw materials, i.e. straight-run gasoline produced at the primary oil refining unit; a catalytic reforming unit, where the octane number of hydrotreated gasoline is increased; unit for deethanization and stabilization of catalyzate; unit for cleaning circulating hydrocarbon-containing gases with monoethanolamine (MEA) and MEA regeneration.

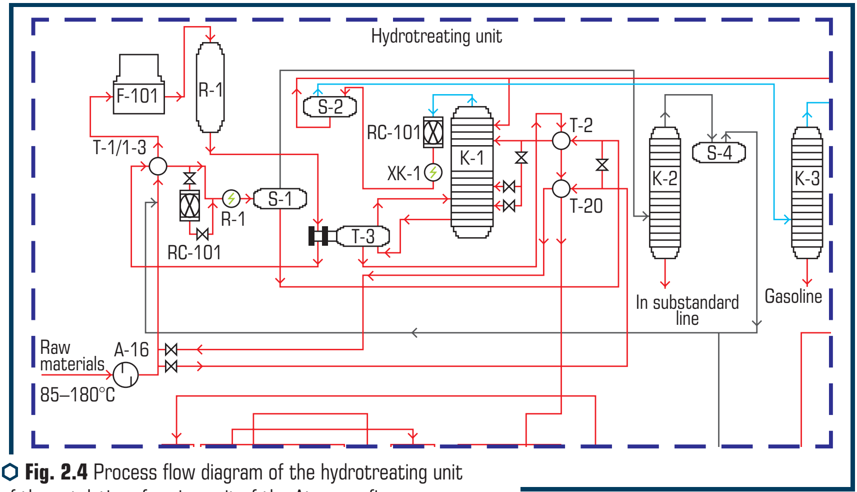


Fig. 2.4 Process flow diagram of the hydrotreating unit of the catalytic reforming unit of the Atyrau refinery

Raw materials from the tank farm are fed by the A16 pump for mixing together with the WASH. The mixture of raw materials and HCG is fed to 3 heat exchangers T-1/1-3 connected in series, here, due to the counterflow of carbonated raw materials from the R-1 reactor and the T-3 reboiler, it is heated to a temperature of 260 °C, then further fed to the F-101 hydrotreating furnace. From the F-101 furnace, a mixture of raw materials and gas with a temperature of 300–343 °C is fed to the R-1 hydrotreating reactor. In the reactor R-1 with the participation of catalyst C-12, the reaction of hydrotreating the raw material proceeds, i.e. the raw material is preliminarily hydrotreated to remove sulfur, nitrogen and oxygen-containing compounds. The heat of the mixture of unstable hydrogenate, circulating gas from the outlet of the reactor and the heat of reaction of gases with a temperature of 340–420 °C is used to heat the mixture of raw materials and gas, first in the heat exchanger T-3 of the stripping column K-1, then in the heat exchangers T-1/1-3 [76].

The products in the form of gas, after cooling to a temperature of 35 °C in refrigerators RC-101 and R-1, enters the separator S-1. In S-1, HCG is separated from the liquid and fed to the K-2 absorber for purification from hydrogen. Gas from the outlet of the K-2 absorber and after passing through the S-4 separator is divided into two streams:

1) circulating gas, after being compressed in the compressors, which is fed back to the raw material hydrotreating system;

2) Excessive HCG from the outlet of the unit, the liquid phase of the separator S-1 passes through the heat exchanger T-2, here it is heated to a temperature of 150 °C and floats on 7, 9, 23 trays of the K-1 stripping column. From the column K-1, which has 30 trays, from the hydrogenation product at a temperature of up to 270 °C and a pressure of up to 15 atm, sulfuric hydrogen and water are stripped, in addition, light hydrocarbons are removed from the top of the column.

After the stripping column K-1, the total composition of sulfur compounds in the hydrogenation product should not exceed 0.0005 % of the mass. Gases in the state of vapor from the top of the column K-1 come out with a temperature of 135 °C, pass through the chimney-condensers ACRC-101 and RC-1 and with a temperature of 35–40 °C are fed to the separator S-2. From the separator S-2, the liquid phase is returned to the stripping column K-1. The precipitated water in the S-2 separator is discharged into the sewerage system. Hydrocarbon gas from the S-2 separator for hydrogen sulfide removal enters the K-3 absorber. Hydrocarbon gas from the top of the K-3 absorber is fed into the K-6 fractionating absorber or the plant's fuel network. Thus, in the hydrotreating process, a chemical transformation of a substance occurs under the influence of hydrogen gas with high pressure and high temperature. In the process of hydrotreating, sulfur compounds are reduced in the composition of petroleum products and fuels, additional unsaturated hydrocarbons are saturated, the composition of tar, oxygenated compounds decreases, as well as hydrocracking of hydrocarbon molecules. Improvement of refinery hydrotreating processes using modelling methods allows [77]:

– carrying out hydrotreating processes in the optimal mode;

– improvement of quality indicators of manufactured products.

In this paper, the first direction of improving the hydrotreating processes is considered in more detail, using the example of the hydrotreating block of the catalytic reforming unit of the Atyrau refinery. Known research works on methods of mathematical modelling and optimization of technological objects and oil refining processes, incl. hydrotreating process. However, in practice, production situations can often arise associated with a shortage and indistinctness of initial information, problems of modelling and optimization of their operation modes, the formulation and solution of which using traditional methods does not provide adequate solutions. Such objects include the hydrotreating unit of the LG unit of the Atyrau refinery, the main units of which operate under conditions of uncertainty associated with randomness and with indistinctness of initial information.

The purpose of this section of the work is to develop a system of mathematical models of the main units of the hydrotreating unit of the catalytic reforming unit of the Atyrau refinery based on the available information of a different nature, which can be used to optimize the process parameters and control the operating modes of the hydrotreating unit.

In order to create a system for optimizing and controlling the operating modes of the hydrotreating unit of the catalytic reforming unit, it is necessary to develop a system of mathematical models of the main interconnected units of this unit, namely, the R-1 hydrotreating reactor, K-1 steam column, K-2 and K-3 absorbers, as well as hydrotreating furnaces F-101. When developing mathematical models of the listed main units of the hydrotreating unit, problems may arise associated with a shortage, uncertainty and lack of clarity of initial information. Uncertainty can be caused due to the scarcity, randomness and fuzziness of the available information necessary for the development of mathematical models of objects. In these cases, an appropriate approach will have to be applied, for example, the hybrid method proposed in [72], which allows one to build mathematical models of objects based on the available information of a different nature. Let $\left\{\ddot{x}_i,\ i=\overline{1,l} \text{ and } \tilde{x}_i,\ i=\overline{1,m}\right\}$ be the set of available input parameters of the object, which are characterized by probability – $\ddot{x}$ and fuzziness – $\tilde{x}$. The values $\left\{\ddot{x}_i,\ i=\overline{1,l}\right\}$ are determined using measuring instruments, but are characterized by randomness. Values $\left\{\tilde{x}_i,\ i=\overline{1,m}\right\}$ are evaluated by humans, i.e. specialists-experts on the basis of their knowledge, experience and intuitions is not crisp, i.e. words, phrases and are fuzzy. On the basis of such initial information of a different nature, it is necessary to identify the structures and parameters of the models of the main units of the hydrotreating unit. In this case, one has to use the methods of probability theory, experimental statistical methods for developing models, as well as with modified and adapted for working in a fuzzy environment known methods, for example, the method of sequential inclusion of regressors [70], and the method of least squares [36], as well as hybrid the method of building models [72, 76].

Thus, on the basis of the above methods, it is necessary to develop a system of mathematical models of the R-1 hydrotreating reactor, columns K-1, K-2 and K-3, as well as the F-101 hydrotreating furnace. For R-1 it is necessary to identify equations that allow calculating the values of the output parameters of the reactor: y_1 – volume of hydrogenated product; and evaluating the values of the quality indicators of the product: $\tilde{y}_2, \tilde{y}_3$ and $\tilde{y}_4$ – respectively, unsaturated hydrocarbons, sulfur and water-soluble acids and alkalis in the hydrogenated product. For columns K-1, K-2 and K-3, it is necessary to identify models that allow determining the yield of hydrogenated product from K-1, HCG from K-2 and hydrocarbon-containing gas from K-3, as well as evaluating the main quality indicators of the column products from the input parameters columns. And the mathematical models of the F-101 hydrotreating furnace must determine the volume of raw material with gas and the temperature of the flow from the outlet of the pesh, depending on the values of the F-101 input parameters.

Mathematical models of the main units of the hydrotreating unit based on statistical and fuzzy information. To solve the problem, i.e. to develop a system of mathematical models of the main units of the hydrotreating unit, which determine the dependence of the unit's output parameters (product, its quality) on the input, operating parameters, let's use the available information of a different nature.

For example, for the development of mathematical models of the hydrotreating reactor, which make it possible to determine the volume of hydrogenated product from the outlet of the hydrotreating reactor R-1, experimental statistical data are used, characterized by probability, and expert information of a fuzzy nature. For the structural identification of the R-1 reactor models, the idea of the method of sequential switching on of regressors is used, and the identification of the model parameters is carried out on the basis of a modified least squares method. Thus, the mathematical models of the R-1 reactor of the hydrotreating blog are developed using statistical data and fuzzy information, processed by the methods of mathematical statistics and the theory of fuzzy sets. Fuzzy information is collected and formalized by expert assessment methods and fuzzy set theories.

Based on the processing of experimental statistical data and expert information, as well as using the method of building fuzzy models [36], the structural identification of the models describing the product quality of the R-1 hydrotreating reactor was carried out in the form of the following fuzzy multiple regression equations:

$$\tilde{y}_j = a_{0j}x_{ij} + \sum_{i=1}^{5} a_{ij}x_{ij} + \sum_{i=1}^{5}\sum_{k=i}^{5} a_{ijk}x_{ij}x_{kj},\ j=\overline{2,4}, \tag{2.6}$$

where $\tilde{y}_2$ – unsaturated hydrocarbons in the composition of the product, i.e. hydrogenate (should be no more, i.e. $\tilde{\leq}1$ %); $\tilde{y}_3$ – sulfur in the hydrogenated product ($\tilde{\leq}0.00005$ %); $\tilde{y}_4$ – water-soluble acids and alkalis in the hydrogenated product ($\tilde{\cong}0$ %); x_1 – raw materials, in our case, straight-run gasoline (45–80 m^3/hour); x_2 – pressure in the reactor (20–35 kg/cm^2); x_3 – temperature in the reactor (300–343 °C); x_4 – volumetric raw material rate (0.5–5 h^{-1}); x_5 – circulating hydrogen-containing gases (HCG) – hydrogen/hydrocarbon ratio (200–500 nm^3); $\tilde{a}_{0j}$, $\tilde{a}_{ij}$, $\tilde{a}_{ikj}$, $i=\overline{1,5}$ – identifiable fuzzy coefficients coefficients, respectively: the leading term; linear influences; square influences and reciprocal influences. The admissible fuzzy values of the output parameters, as well as the intervals for changing the input and operating parameters, are indicated in brackets.

To describe the product quality of the R-1 hydrotreating reactor, building a model in the form of fuzzy multiple regression equations (2.6) is justified by the fact that the qualitative indicators of the hydrotreating (hydrogenated product) product are not directly quantitatively measured in practice, but rather indistinctly assessed by laboratory assistants and specialists of the plant laboratory. In this case, the input, mode parameters influencing the quality of the hydrogenate are quantitatively measured. Therefore, in accordance with the fuzzy model synthesis method described in Section 2.4 above, to describe the quality of the hydrogenated product, models in the form of fuzzy multiple regression equations have been built.

To identify unknown parameters (regression coefficients) of model (1): $\tilde{a}_{ij}\left(i=\overline{0,5},\ j=\overline{2,5}\right)$ and $\tilde{a}_{ikj}\left(i,k=\overline{1,5},\ j=\overline{2,5}\right)$ – membership functions of fuzzy sets describing the qualities of hydrogenated product are divided into the following sets of level α: α=0.5; 0.85; 1. As substantiated by the authors of [145], in which the triangular function is approximated by the Gaussian function, for practical application, the membership function in the Gaussian form is more convenient. In addition, the membership function of the Gauss type makes it possible to more adequately display the degree of membership of elements to a fuzzy set on the graph, i.e. fuzzy representation of a person, which is non-linear. In this regard, there are selected and built accessory functions that have a bell-shaped, i.e. Gaussian view. Therefore, the obtained values of fuzzy parameters at 5 points α=0.5; 0.85 (left); 1; 0.85; 0.5 (right). This is due to the fact that the Gaussian type membership function has a symmetrical form. Therefore, when carrying out α sections, they cut through the graph of the membership function on the left and right sides at levels α=0.5; 0.85. The values of the input, mode $x_{ij},\ i,j=\overline{1,5}$ and output $\tilde{y}_2$, $\tilde{y}_3$, $\tilde{y}_4$ parameters for each selected α level are observed. Thus, the models describing the quality of the product from the outlet of the R-1 reactor in the form of multiple regression for each α level are obtained. Since the obtained equations have the form of regression equations, the problem of identifying their unknown coefficients $\alpha_{ij}^{\alpha_q}$, $i=\overline{0,5}$, $j=\overline{2,4}$, $q=\overline{1,3}$ can be solved using well-known parametric identification methods, for example, using the least squares method. In this work, to identify the regression coefficients, the REGRESS program package was used, which, based on modified least squares methods, allows one to determine the regression coefficients of linear and nonlinear regression models with any number of input parameters x_i, $i=\overline{1,n}$.

Thus, after parametric identification, mathematical models describing the influence of input, operating parameters x_i, $i=\overline{1,n}$ on the quality of the hydrogenated product, i.e. on the content of unsaturated hydrocarbons $\left(\tilde{y}_2\right)$, sulfur $\left(\tilde{y}_3\right)$ and water-soluble acids and alkalis $\left(\tilde{y}_4\right)$ for each a level has the form:

$$y_2=\left(\frac{0.5}{0.05}+\frac{0.85}{0.07}+\frac{1}{0.08}+\frac{0.85}{0.09}+\frac{0.5}{0.095}\right)-$$

$$-\left(\frac{0.5}{0.00215}+\frac{0.85}{0.0029}+\frac{1}{0.00324}+\frac{0.85}{0.00375}+\frac{0.5}{0.00425}\right)x_1+$$

$$+\left(\frac{0.5}{0.00591}+\frac{0.85}{0.00592}+\frac{1}{0.00593}+\frac{0.85}{0.00594}+\frac{0.5}{0.00595}\right)x_2+$$

$$+\left(\frac{0.5}{0.0002}+\frac{0.85}{0.0005}+\frac{1}{0.0007}+\frac{0.85}{0.00095}+\frac{0.5}{0.0013}\right)x_3-$$

$$-\left(\frac{0.5}{0.03125}+\frac{0.85}{0.04333}+\frac{1}{0.05333}+\frac{0.85}{0.06333}+\frac{0.5}{0.007333}\right)x_4+$$

$$+\left(\frac{0.5}{0.0004}+\frac{0.85}{0.0005}+\frac{1}{0.0006}+\frac{0.85}{0.0007}+\frac{0.5}{0.0008}\right)x_5-$$

$$-\left(\frac{0.5}{0.00002}+\frac{0.85}{0.00003}+\frac{1}{0.00004}+\frac{0.85}{0.00005}+\frac{0.5}{0.00007}\right)x_1^2+$$

$$+\left(\frac{0.5}{0.00021}+\frac{0.85}{0.00022}+\frac{1}{0.00023}+\frac{0.85}{0.00024}+\frac{0.5}{0.00025}\right)x_2^2+$$

$$+\left(\frac{0.5}{0.00012}+\frac{0.85}{0.00018}+\frac{1}{0.00023}+\frac{0.85}{0.00028}+\frac{0.5}{0.00033}\right)x_3^2-$$

$$-\left(\frac{0.5}{0.01675}+\frac{0.85}{0.01727}+\frac{1}{0.01777}+\frac{0.85}{0.01713}+\frac{0.5}{0.01818}\right)x_4^2+$$

$$+\left(\frac{0.5}{0.000008}+\frac{0.85}{0.000014}+\frac{1}{0.00002}+\frac{0.85}{0.00003}+\frac{0.5}{0.00005}\right)x_5^2-$$

$$-\left(\frac{0.5}{0.0003}+\frac{0.85}{0.00035}+\frac{1}{0.0004}+\frac{0.85}{0.00045}+\frac{0.5}{0.0005}\right)x_1x_2+$$

$$+\left(\frac{0.5}{0.000024}+\frac{0.85}{0.00003}+\frac{1}{0.000033}+\frac{0.85}{0.00004}+\frac{0.5}{0.000047}\right)x_1x_3-$$

$$-\left(\frac{0.5}{0.00068}+\frac{0.85}{0.0007}+\frac{1}{0.00073}+\frac{0.85}{0.00075}+\frac{0.5}{0.00077}\right)x_1x_4+$$

$$+\left(\frac{0.5}{0.000012}+\frac{0.85}{0.000019}+\frac{1}{0.000027}+\frac{0.85}{0.000035}+\frac{0.5}{0.000043}\right)x_1x_5-$$

$$-\left(\frac{0.5}{0.00083}+\frac{0.85}{0.0009}+\frac{1}{0.00098}+\frac{0.85}{0.0001}+\frac{0.5}{0.0015}\right)x_2x_4+$$

$$+\left(\frac{0.5}{0.000005}+\frac{0.85}{0.000006}+\frac{1}{0.000007}+\frac{0.85}{0.000008}+\frac{0.5}{0.000009}\right)x_2x_5-$$

$$-\left(\frac{0.5}{0.0001}+\frac{0.85}{0.00015}+\frac{1}{0.00012}+\frac{0.85}{0.00015}+\frac{0.5}{0.00018}\right)x_3x_5;$$

$$y_3 = \left(\frac{0.5}{0.002} + \frac{0.85}{0.003} + \frac{1}{0.004} + \frac{0.85}{0.005} + \frac{0.5}{0.006} \right) -$$

$$- \left(\frac{0.5}{0.00014} + \frac{0.85}{0.00015} + \frac{1}{0.00016} + \frac{0.85}{0.00017} + \frac{0.5}{0.00018} \right) x_1 +$$

$$+ \left(\frac{0.5}{0.00027} + \frac{0.85}{0.00028} + \frac{1}{0.00029} + \frac{0.85}{0.0003} + \frac{0.5}{0.00031} \right) x_2 +$$

$$+ \left(\frac{0.5}{0.00002} + \frac{0.85}{0.00003} + \frac{1}{0.00004} + \frac{0.85}{0.000045} + \frac{0.5}{0.0005} \right) x_3 +$$

$$+ \left(\frac{0.5}{0.000001} + \frac{0.85}{0.0000015} + \frac{1}{0.000002} + \frac{0.85}{0.0000025} + \frac{0.5}{0.000003} \right) x_1^2 +$$

$$+ \left(\frac{0.5}{0.00001} + \frac{0.85}{0.000015} + \frac{1}{0.00002} + \frac{0.85}{0.000025} + \frac{0.5}{0.00003} \right) x_2^2 +$$

$$+ \left(\frac{0.5}{0.00015} + \frac{0.85}{0.00017} + \frac{1}{0.00018} + \frac{0.85}{0.00019} + \frac{0.5}{0.0002} \right) x_4^2 +$$

$$+ \left(\frac{0.5}{0.00002} + \frac{0.85}{0.00003} + \frac{1}{0.00004} + \frac{0.85}{0.00005} + \frac{0.5}{0.00006} \right) x_1 x_2 +$$

$$+ \left(\frac{0.5}{0.000001} + \frac{0.85}{0.000009} + \frac{1}{0.00001} + \frac{0.85}{0.00002} + \frac{0.5}{0.00003} \right) x_1 x_3 -$$

$$- \left(\frac{0.5}{0.00007} + \frac{0.85}{0.00013} + \frac{1}{0.00018} + \frac{0.85}{0.00023} + \frac{0.5}{0.00030} \right) x_1 x_4 +$$

$$+ \left(\frac{0.5}{0.00001} + \frac{0.85}{0.00009} + \frac{1}{0.00010} + \frac{0.85}{0.00020} + \frac{0.5}{0.00030} \right) x_2 x_3 -$$

$$- \left(\frac{0.5}{0.00038} + \frac{0.85}{0.00044} + \frac{1}{0.00049} + \frac{0.85}{0.00054} + \frac{0.5}{0.00064} \right) x_2 x_4 +$$

$$+ \left(\frac{0.5}{0.000002} + \frac{0.85}{0.000003} + \frac{1}{0.000004} + \frac{0.85}{0.000005} + \frac{0.5}{0.000006} \right) x_3 x_4;$$

$$y_4=\left(\frac{0.5}{0.00023}+\frac{0.85}{0.00024}+\frac{1}{0.00025}+\frac{0.85}{0.00026}+\frac{0.5}{0.00027}\right)-$$

$$-\left(\frac{0.5}{0.001}+\frac{0.85}{0.0015}+\frac{1}{0.002}+\frac{0.85}{0.0025}+\frac{0.5}{0.003}\right)x_1-$$

$$-\left(\frac{0.5}{0.00024}+\frac{0.85}{0.00032}+\frac{1}{0.00037}+\frac{0.85}{0.00042}+\frac{0.5}{0.005}\right)x_2-$$

$$-\left(\frac{0.5}{0.00003}+\frac{0.85}{0.00004}+\frac{1}{0.00005}+\frac{0.85}{0.00006}+\frac{0.5}{0.00007}\right)x_3+$$

$$+\left(\frac{0.5}{0.00659}+\frac{0.85}{0.00664}+\frac{1}{0.00667}+\frac{0.85}{0.00670}+\frac{0.5}{0.00675}\right)x_4+$$

$$+\left(\frac{0.5}{0.000002}+\frac{0.85}{0.000003}+\frac{1}{0.000004}+\frac{0.85}{0.000005}+\frac{0.5}{0.000006}\right)x_5-$$

$$-\left(\frac{0.5}{0.000001}+\frac{0.85}{0.000005}+\frac{1}{0.00001}+\frac{0.85}{0.000015}+\frac{0.5}{0.000020}\right)x_2^2+$$

$$+\left(\frac{0.5}{0.000207}+\frac{0.85}{0.000215}+\frac{1}{0.000222}+\frac{0.85}{0.000230}+\frac{0.5}{0.000330}\right)x_4^2+$$

$$+\left(\frac{0.5}{0.000001}+\frac{0.85}{0.000005}+\frac{1}{0.00001}+\frac{0.85}{0.000015}+\frac{0.5}{0.000020}\right)x_1x_2-$$

$$-\left(\frac{0.5}{0.000005}+\frac{0.85}{0.00001}+\frac{1}{0.00002}+\frac{0.85}{0.00003}+\frac{0.5}{0.00004}\right)x_1x_4+$$

$$+\left(\frac{0.5}{0.000004}+\frac{0.85}{0.000005}+\frac{1}{0.000006}+\frac{0.85}{0.000007}+\frac{0.5}{0.000008}\right)x_2x_4-$$

$$-\left(\frac{0.5}{0.000001}+\frac{0.85}{0.000005}+\frac{1}{0.000001}+\frac{0.85}{0.0000015}+\frac{0.5}{0.00002}\right)x_3x_4+$$

$$+\left(\frac{0.5}{0.0000001}+\frac{0.85}{0.0000005}+\frac{1}{0.0000010}+\frac{0.85}{0.0000015}+\frac{0.5}{0.0000020}\right)x_4x_5.$$

The identified values of the coefficients $a_{ij}^{\alpha_q}$, $i=\overline{0,5}$; $j=\overline{2,4}$; $q=\overline{1,3}$ are combined using the following expression of fuzzy set theories [108]:

$$a_{ij}=\bigvee_{\alpha\in[0.5,1]} a_{ij}^{\alpha_q} \text{ or } \mu\,\tilde{a}_{ij}\left(a_{ij}\right)=\text{SUP}\min_{\alpha\in[0.5,1]}\left\{\alpha,\mu\,a_{ij}^{\alpha}\left(a_{ij}\right)\right\},$$

where

$$a_{ij}^{\alpha_q} = \left\{ a_i \middle| \mu \tilde{a}_{ij} \left(a_{ij} \right) \right\}.$$

In the obtained models, the regressors that have no effect on $\tilde{y}_2$, $\tilde{y}_3$, $\tilde{y}_4$ or have a very weak effect are zeroed, i.e. not shown.

As a result of the conducted research and processing of data results, it was determined that to determine the volume of product output from the R-1 reactor, i.e. volume of hydrogenated product y_1 – on the basis of experimental and statistical data, it is possible to build a statistical model, which, using a nonlinear regression equation, makes it possible to estimate the values y_1 from the input and operating parameters x_i, $i = \overline{1,5}$. After identifying the structure and parameters of this model, similar to the above-described approach, the mathematical model that allows determining the volume of hydrogenate from the outlet of the R-1 reactor has the form:

$$y_1 = 7.00 + 0.233x_1 + 0.130x_2 + 0.011x_3 + 2.333x_4 - 0.0175x_5 + 0.0031x_1^2 +$$

$$+0.0048x_2^2 + 0.00003x_3^2 + 0.7778x_4^2 - 0.00004x_5^2 + 0.0017x_1x_2 + 0.00015x_1x_3 +$$

$$+0.03111x_1x_4 + 0.00023x_1x_5 + 0.08642x_2x_4 - 0.00065x_2x_5 + 0.00730x_3x_4.$$

A graph of the dependence of the hydrogenated product yield on the temperature in the reactor x_3 at fixed values of the raw material input and other operating parameters is built: x_1, x_2, x_4 and x_5 (**Fig. 2.5**).

Studies of the influence of other operating parameters x_1, x_2, x_4 and x_5 and their mutual influence on the output parameters of the reactor will be carried out.

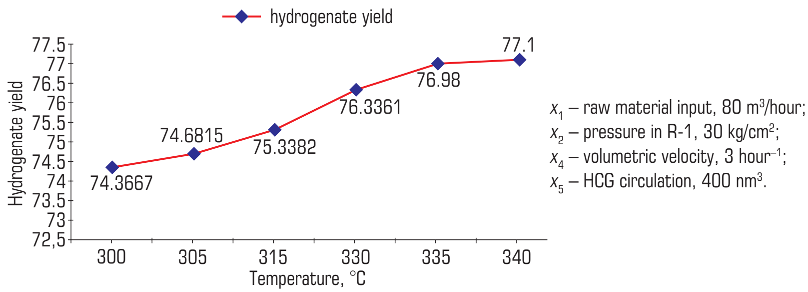


Fig. 2.5 Dependency graph $y_1 = f_1(x_3)$ for fixed x_1, x_2, x_4 and x_5

To determine the optimal temperature of the hydrotreating process on the basis of expert information and a logical rule of conditional conclusions and a rule base, a linguistic model has been built. The resulting linguistic model implements the logical dependence: «*If the raw material is heavy*, then the process temperature is *low*, otherwise, if the raw material is *light*, then the process temperature is *high*».

On the basis of expert judgment and using the methods of fuzzy set theories in the form of an exponential dependence, membership functions are built that describe the fuzzy parameters of the linguistic model:

$\mu_A(h) = \exp\left(\left|(ts - 185)^{0.5}\right|\right)$ – heavy (low thermal stability) raw material – straight-run gasoline;

$\mu_A(l) = \exp\left(\left|(ls - 165)^{0.5}\right|\right)$ – light raw material;

$\mu_B(l) = \exp\left(\left|(nt - 300)^{0.5}\right|\right)$ – low temperature;

$\mu_B(h) = \exp\left(\left|(vt - 400)^{0.5}\right|\right)$ – high temperature.

Thus, the structure of the linguistic model that estimates the optimal temperature depending on the quality of raw materials:

$$If\ \ \tilde{x}_1 \in \overleftrightarrow{A}_1 \wedge \tilde{x}_2 \in \overleftrightarrow{A}_2 \wedge \ldots \wedge \tilde{x}_n \in \overleftrightarrow{A}_n,\ Then\ \ \tilde{y}_j \in \tilde{B}_j,\ j = \overline{1,m},$$

is defined using logical rules of conditional inference:

$$If\ \ \tilde{x}_1 \in \tilde{A}(ts)\ Then\ \ \tilde{y} \in \tilde{B}(nt),\ Else\ \ If\ \ \tilde{x} \in \tilde{A}(ls),\ Then\ \ \tilde{y} \in \tilde{B}(vt).$$

In the resulting linguistic model, the following designations are introduced: *ts, ls, nt, vt* – respectively, «heavy raw materials»; «light raw materials»; «Low temperature» and «High temperature»; $\tilde{x}$, $\tilde{y}$ – respectively, input and output linguistic variables that describe the quality of raw materials and the optimum temperature of the hydrotreating process; $\tilde{A}$, $\tilde{B}$ – fuzzy subsets describing $\tilde{x}$ and $\tilde{y}$.

Let's present the results of the development of *mathematical models of columns* K-1, K-2 and K-3, which are also related to the main units of the hydrotreating unit.

The stripping column K-1 of the hydrotreating unit is designed to separate water vapor and hydrogen sulfide from the product, i.e. from the hydrogenate. The composition of sulfur compounds in products should not exceed 0.0005 % wt. Column K-2 of the hydrotreating unit is an absorber designed for the purification of hydrogen from hydrocarbon gases. Column K-3 of the hydrotreating unit is also an absorber in which hydrogen sulphide is purified from hydrocarbon gases.

As a result of the study of the operating modes of the columns K-1, K-2, K-3 and data analysis, as well as taking into account additional fuzzy information received from experts for the development of mathematical models of these columns, it was decided to use a hybrid method of model development.

Based on the research data of the K-1, K-2 and K-3 columns and the results of the expert assessment, the following input (x) and output (y) parameters were identified, describing the modes of their operation:

x_1 – volume of raw materials at the inlet of the columns;

x_2 – inlet temperature;

x_3 – column pressure;

x_4 – irrigation volume of the column K-1;

y_1 – volume of hydrogenated product from the outlet of the column K-1;

y_2 – volume of WASH from the outlet of the column K-2;

y_3 – volume of hydrocarbon-containing gas from the outlet of the column K-3;

$\tilde{y}_4$ – composition of hydrogenated sulphide compounds, quality of K-1 product;

$\tilde{y}_5$ – HCG composition, product quality of column K-2;

$\tilde{y}_6$ – composition of hydrocarbon-containing gas, product quality of column K-3.

Column input parameters x_1, x_2, x_3, x_4, i.e. raw material flow rates, inlet temperature, pressure in the columns and reflux volume of column K-1, and output parameters y_1, y_2, y_3 describing the volumes of products at the outlet of the columns are measured parameters. This means that it is possible to collect statistical data on these parameters: $x_i,\ i=\overline{1,4}$; $y_j,\ i=\overline{1,3}$. A quality indicators of products produced in columns K-1, K-2 and K-3: $\tilde{y}_j,\ j=\overline{4,6}$ are not clearly described. Therefore, these fuzzy quality indicators are evaluated by experts, formalized and processed using the methods of fuzzy set theories.

Thus, the structures of the mathematical models of the stripping column K-1, absorbers K-2 and K-3 of the hydrotreating unit are identified based on the method of sequential inclusion of regressors and its modification in the form of the following nonlinear regression and fuzzy regression equations:

$$y_j = a_{0j} + \sum_{i=1}^{4} a_{ij}x_{ij} + \sum_{i=1}^{4}\sum_{k=i}^{4} a_{ikj}x_{ij}x_{kj},\ j=\overline{1,3}; \tag{2.7}$$

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{4} \tilde{a}_{ij}x_{ij} + \sum_{i=1}^{4}\sum_{k=i}^{4} \tilde{a}_{ikj}x_{ij}x_{kj},\ j=\overline{4,6}. \tag{2.8}$$

Parameter identification, i.e. regression coefficients a_{0j}, a_{ij}, a_{ikj}, $i=\overline{1,4};\ k=\overline{i,4};\ j=\overline{1,3}$ of regression models (2.7) is carried out on the basis of the least squares method using the statistical data of the object.

To identify fuzzy parameters $\tilde{a}_{0j}$, $\tilde{a}_{ij}$, $\tilde{a}_{ikj}$, $i=\overline{1,4};\ k=\overline{i,4};\ j=\overline{4,6}$ of fuzzy regression models (2.8) based on a set of level a, fuzzy equations are transformed into a system of crisp equations that are equivalent to the original fuzzy equations. Then, similarly to the procedure for identifying fuzzy parameters of model (2.5) of the R-1 reactor, based on the least squares method according to the criterion of minimizing the mismatch between the model and experimental (real) data, fuzzy coefficients for different levels of the set a are identified.

To determine the volume of the target product of the K-1 column, i.e. hydrogenated product after parametric identification of model (2.7) at $j=1$, the following results were obtained:

$$y_1 = f_1(x_{11}, x_{21}, x_{31}, x_{41}) = -3.65 + 0.2433x_{11} + 0.0365x_{21} + 1.8250x_{31} - \\ -1.3272x_{41} + 0.0018x_{11}^2 + 0.00009x_{21}^2 - 0.1141x_{31}^2 - 0.0603x_{41}^2 + 0.00041x_{11}x_{21} + \\ +0.02027x_{11}x_{31} + 0.00456x_{21}x_{31}.$$

Also, using the methods of sequential inclusion of regressors and least squares, the structures (2) and parameters of the absorber columns K-2 and K-3 were identified, i.e. determined the volume of HCG from the absorber K-2 (y_2) and the output of hydrocarbon-containing gas from the column K-3 (y_3):

$$y_2 = f_2(x_{12}, x_{22}, x_{32}) = 84.9999 + 0.2982x_{12} + 2.8333x_{22} - 2.4285x_{32} + 0.0001x_{12}^2 + \\ +0.0944x_{22}^2 - 0.0694x_{32}^2 - 0.0066x_{12}x_{22} - 0.0028x_{12}x_{32} + 0.2428x_{22}x_{23};$$

$$y_3 = f_3(x_{13}, x_{23}, x_{33}) = 83.4999 + 0.2973x_{13} + 2.7833x_{23} - 7.5909x_{33} - 0{,}0001x_{13}^2 + \\ + 0.0927x_{23}^2 - 0.6901x_{33}^2 - 0.0065x_{13}x_{23} + 0.0090x_{13}x_{33} + 0.7591x_{23}x_{33}.$$

Similarly to models (2.6) for assessing the quality indicators of hydrogenated product $\tilde{y}_2$, $\tilde{y}_3$, $\tilde{y}_4$, it is possible to identify fuzzy parameters of models (2.8) assessing the quality of products from columns K-1, K-2 and K-3: $\tilde{y}_j$, $j = \overline{4,6}$.

Mathematical models of the F-101 hydrotreating furnace of the hydrotreating unit.

The cylindrical hydrotreating furnace F-101 is designed for heating the hydrotreating product, i.e. hydrogenizate to the temperature required by the regulation.

Based on the results of research and analysis, the following main parameters have been identified that affect the operation of the F-101 furnace and the hydrotreating process:

x_1 – consumption, volume of raw materials at the entrance of the F-101 furnace, in the range of 60–80 m^3/h;

x_2 – temperature at the inlet of the F-101 furnace, within the range of 170–190 °C;

x_3 – pressure in the F-101 furnace, in the range 40–43 kg/cm^2.

As a result of the analysis of the collected data and the study of the operating modes of the hydrotreating furnace for the development of its model, an experimental-statistical method was chosen. The optimal operating mode of the furnace can be selected on the basis of a mathematical model describing the influence of input variables on the output parameters, i.e. allowing to get information about the thermal operation of the furnace. The mathematical description, which is the basis of the mathematical model, must determine the parameters of the thermal operation of the furnace [68].

The main disadvantage of the methods for calculating furnaces used to date is that in these methods only integral indicators of the heat transfer process are determined, they do not determine the possibility of heating the furnace tubes. Recently, modelling methods based on theoretical studies have been proposed, which make it possible to determine local heat transfer parameters, for example, the zonal method. In mathematical terms, the meaning of the zonal calculation method is the replacement of integral-differential equations describing the process of heat transfer, with a limited system of algebraic equations approximating them. By solving the obtained algebraic equations, the energy characteristics of heat transfer are determined, i.e. temperature and flows of local zones. For this purpose, research furnaces are divided into a limited number of areal and volumetric zones with the same radiation properties. This approach in calculating the furnace can provide sufficient accuracy; to increase the accuracy, it is necessary to increase the number of zones. However, this method is rather complicated and the collection of the necessary information for its application in practice is also difficult.

To simulate the operation of industrial furnaces in an interactive mode and to quickly obtain the necessary information and results, simple models are required. For this reason, the analytical method of *N*. Belokan, based on a joint solution of the heat transfer equation and heat balance [68].

Regression models were identified to calculate the output parameters of the P-101 hydrotreating furnace on the basis of statistical and experimental data. In this case, the distribution law of random measurements in accordance with the source [71] can be considered close to the normal law; $M\left[\varepsilon_j\right]=0,\ \gamma=\left(\gamma_1,\ldots,\gamma_m\right),\ j=\overline{1,m}.$

Thus, the structure of the model that estimates the yield of the hydrotreating furnace: the volume of the mixture of raw material and gas and the temperature of the outlet flow from the furnace, are identified in the form of the following nonlinear regression equations:

$$\begin{aligned} y_j &= a_{0j}+a_{1j}x_1+a_{2j}x_2+a_{3j}x_3+a_{4j}x_1^2+a_{5j}x_2^2+a_{6j}x_3^2+ \\ &+a_{7j}x_1x_2+a_{8j}x_1x_3+a_{9j}x_2x_3+\varepsilon_j,\ j=1,2. \end{aligned} \tag{2.9}$$

In the model (2.9), the following designations are adopted: $a_{ij},\ i=\overline{0,3},\ j=1,2$ – the parameters of the model, which must be identified, for their estimation, one can use the well-known method of least squares; $x_1,\ x_2,\ x_3$ – operating parameters of the F-101 furnace, respectively: the volume of raw materials $\left(x_1\right)$; temperature at the furnace inlet $\left(x_2\right)$ and pressure in the F-101 furnace $\left(x_3\right)$.

Results of identification of regression coefficients of model (4) using processed statistical data and using the REGRESS program:

$$\begin{aligned} y_1 &= 3.7500+0.2922x_1+0.0208x_2-0.0893x_3+0.0025_1^2+0.0001x_2^2+ \\ &+0.0021x_3^2+0.0011x_1x_2+0.0023x_1x_3+0.0045x_2x_3; \end{aligned}$$

$$\begin{aligned} y_2 &= 17.0000-0.2208x_1+0.7555x_2+0.4047x_3-0.0028_1^2+0.0016x_2^2- \\ &-0.0096x_3^2+0.0037x_1x_2+0.0157x_1x_3+0.0045x_2x_3. \end{aligned}$$

As a result of system analysis and expert assessments, it was determined that for heat exchangers and separators of a hydrotreating unit, the most effective are, respectively, the development of statistical and deterministic models using appropriate methods.

The approach proposed above to the development of mathematical models of a complex of interconnected technological objects on the basis of available information of various types makes it possible to develop models of real technological objects in conditions of a deficit and indistinctness of initial information.

The structures of the developed mathematical models of the main units of the hydrotreating unit: reforming reactor R-1, columns K-1, K-2 and K-3, reforming furnaces F-101 are identified in the form of nonlinear regression equations. In this case, the equations describing the volume of production from the units are in the form of the usual equation of multiple regression, and the equations describing the qualitative indicators of production from the main units (the content of unsaturated hydrocarbons – $\tilde{y}_2$, sulfur – $\tilde{y}_3$ and water-soluble acids and alkalis – $\tilde{y}_4$; the quality of products from the columns K-1, K-2 and K-3: $\tilde{y}_j$, $j=\overline{4,6}$) look like fuzzy multiple regression equations.

In conditions of indistinctness of both input and output parameters, i.e. when the input and output of the hydrotreating reactor are described by linguistic variables, it is proposed to build linguistic models based on logical rules of a conventional form. This approach was implemented when building a linguistic model describing the dependence of the value of the optimal temperature of the hydrotreating process on the quality indicators of the raw material. At the same time, to build the membership function of fuzzy parameters, an exponential dependence was chosen, which has adjustment coefficients for a more adequate description of the function. The developed models can be used to optimize the process parameters, to select the optimal operating modes of the facility and to control the hydrotreating process.

Thus, in this section, the results of a study of the basis of hydrotreating processes are presented, and the main directions of modernization and improvement of hydrotreating in refineries are highlighted. The main results obtained in the direction of carrying out hydrotreating processes in the optimal mode based on the development and modelling of the operating modes of the hydrotreating reactor are presented.

Mathematical models of the main units of the hydrotreating unit of the R-1 reactor have been developed; stripping columns and absorbents K-1, K-2, K-3; reforming furnaces F-101 of the catalytic cracking unit of the Atyrau refinery, which are characterized by a deficit and fuzzy initial information. To solve the problems of the lack of initial information and the development of mathematical models, it is proposed to use the available information of a different nature using a hybrid method of developing models. Mathematical models of the main units of the hydrotreating unit are developed on the basis of experimental statistical data and fuzzy information from experts. Mathematical models for determining the volume of products from the output of the aggregates are identified in the form of statistical models of the regression type, and the models evaluating the fuzzy described quality indicators of the produced product are identified in the form of fuzzy equations. The structural identification of the developed models was carried out on the basis of the idea of the method of sequential inclusion of regressors, and the parametric identification was carried out using a modified least squares method using the REGRESS software package.

A graph of the dependence of the hydrogenated product yield on the temperature in the R-1 hydrotreating reactor with fixed values of the remaining operating parameters is plotted. Using the linguistic rules of conditional inference, a linguistic model has been built that allows one to describe the dependence of the optimal temperature value on the quality of the raw material.

2.8 BUILDING OF MODELS OF THE MAIN UNITS OF THE CATALYTIC REFORMING UNIT OF THE LG UNIT

Specification and implementation of the above proposed theoretical research results is carried out on the example of the development of mathematical models of the main technological units of the catalytic reforming unit of the LG unit of the Atyrau refinery. Let's investigate the main parameters of this unit and their influence on the technological process [136], on the basis of which mathematical models and a package of models of technological units of the reforming unit of the LG unit are built.

Reactor temperature. The temperature maintained in the catalyst bed of the reforming unit is the main control parameter that is used by the refiner to obtain a product of a given quality. Platforming catalysts can operate over a wide temperature range without causing significant deviations from desired product yields and catalyst stability. However, very high temperatures above 543 °C can lead to thermal reactions that will reduce platformate yield and catalyst stability.

Two indicators can be used to determine the temperature in the reactor: the weighted average temperature at the reactor inlet (ATRI) and the weighted average temperature of the catalyst bed (ATCB). These quantities can be calculated as follows:

$$ATRI = TW_{cb} \times TV_c,$$

where TW_{cb} – total weight of the catalyst fractions in the bed; TV_c – temperature value at the entrance to the catalyst bed,

$$ATCB = TW_{cb} \times TV_r.$$

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

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

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

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

Hydrogen/raw material ratio. The hydrogen/raw material ratio (H_2/raw material) is defined as the quotient of separating the number of moles of circulating hydrogen by the number of moles of naphtha loaded into the unit. Recycling hydrogen during platforming is essential to maintain catalyst stability.

In the course of recirculation, the reaction products and condensed substances are washed off the catalyst surface, and hydrogen is delivered to its liberated active centers. Increasing the H_2/raw material ratio will accelerate the passage of the naphtha through the reactor and provide more heat for endothermic reactions. The end result of this will be an increase in stability along with a small positive effect on yield or product quality.

The properties of the processed raw materials. The properties of raw materials, which are one of the essential issues when discussing technological parameters, including properties: fractional composition: beginning of boiling; 50 % boiling point (distillation); content % (vol.) of paraffins (*P*) and naphthenes (*N*) – PIONA determination method.

Raw materials with a low boiling point below 77 °C usually contain significant amounts of C5 and higher hydrocarbons. The pentanes in the raw material will not be able to convert to aromatic hydrocarbons, and therefore, when passing through the reaction zone, they undergo only isomerization reactions if cracked into light gases. Due to their low octane number, they reduce the octane performance of the entire platformate as a whole and lead to the need to maintain a more rigorous platforming process than expected in the case of S4 reforming and higher.

The low end boiling point raw materials contain high concentrations of S6 and S7, which are the most difficult to reformate. High end boiling point raw materials lead to rapid catalyst coking, and they also promote high end boiling platforming.

Mathematical models of reforming reactors R-2, R-3, R-4, 4a. Based on the above research results, let's develop a mathematical description and models of units. The mathematical model of reforming reactors R-2, R-3, R-4, 4a is based on statistical data, expert information processed by TFS methods, as well as equations of material and heat balances.

For example, as a result of processing experimental-statistical and expert data, as well as applying the idea of the method of sequential inclusion of regressors, on the basis of the methods for synthesizing models in a fuzzy environment proposed above in paragraph 2.3 [144, 146], the following structure of the system of equations of multiple, qualitative regression and conditional logical conclusion, which are models of reforming reactors [147]:

$$y_1^{R_2} = a_0 + \sum_{i=1}^{5} a_i x_i^{R2} + \sum_{i=1}^{5}\sum_{k=i}^{5} a_{ik} x_1^{R_2} x_k^{R_2}, \quad (2.10)$$

$$y_1^{R_3} = a_0 + \sum_{i=1}^{5} a_i x_i^{R_3} + \sum_{i=1}^{5}\sum_{k=i}^{5} a_{ik} x_1^{R_3} x_k^{R_3}, \quad (2.11)$$

$$y_1^{R_{4,4a}} = a_0 + \sum_{i=1}^{5} a_i x_i^{R_2\,4,4a} + \sum_{i=1}^{5}\sum_{k=i}^{5} a_{ik} x_1^{R_{4,4a}} x_k^{R_{4,4a}}, \quad (2.12)$$

$$y_j = a_{0j} + \sum_{i=1}^{5} a_{ij} x_{ij} + \sum_{i=1}^{5}\sum_{k=i}^{5} a_{ijk} x_{ij} x_{kj}, \; j = 2,3, \quad (2.13)$$

$$\tilde{y}_j = \tilde{a}_{0j} + \sum_{i=1}^{5} \tilde{a}_{ij} x_{ij} + \sum_{i=1}^{5}\sum_{k=i}^{5} \tilde{a}_{ijk} x_{ij} x_{kj}, \; j = \overline{4,8}, \quad (2.14)$$

where $y_1^{R_2}$, $y_1^{R_3}$, $y_1^{R_{4,4a}}$ – respectively, the volume of catalyzate from the outlet of reactors R-2, R-3 and R-4, 4a; y_j, $j = 2,3$ – respectively the volume of dry gas and HCG; $\tilde{y}_j$, $j = \overline{4,8}$ – quality indicators of catalyzate, respectively, octane number $\tilde{y}_j$, $j = \overline{4,8}$ – not less than 86 according to the motor method), fractional composition ($\tilde{y}_5$ – 10 % distillation – not higher than 70 °C, $\tilde{y}_6$ – 50 % – not higher than 115 °C), saturated vapor pressure ($\tilde{y}_7$ – not more than 500 mm Hg), the actual resin content in mg. for 100 ml of gasoline ($\tilde{y}_8$ – no more than 5.0); x_1 – raw material – hydrogenated product from the hydrotreating unit (50–80 m^3/h); x_2 – space velocity in reactors (1.0–1.5 hr^{-1}); $x_3^{R_2}$, $x_3^{R_3}$, $x_3^{R_{4,4a}}$ – respectively: temperature in reactors R-2 (470–510 °C), R-3 (480–520 °C) and R-4, 4a (490–525 °C); $x_3^{R_2}$, $x_3^{R_3}$, $x_3^{R_{4,4a}}$ – respectively: pressure in reactors R-2 (25–39 kg/cm^2); R-3 (22–35 kg/cm^2) and R-4, 4a (20–30 kg/cm^2); x_5 – ratio of H_2/raw material (300–500 nm^3); a_{0j}, a_{ij}, a_{ikj} and $\tilde{a}_{0j}$, $\tilde{a}_{ij}$, $\tilde{a}_{ikj}$, $i,k = \overline{1,5}$ – identifiable regression coefficients (crisp and fuzzy with the ~ sign), respectively: free term; taking into account linear influences (x_{ij}), square and mutual influences $\left(x_{ij}, x_{kj}\right)$, on the output parameters of the reactor.

As it is possible to see, the models describing the output of the block have the form of multiple regression, respectively, identified by experimental and statistical methods, and the models evaluating the quality of the catalyzate have the form of fuzzy regression equations and are obtained on the basis of qualitative information from experts [148].

The identification of the regression coefficients in the models (2.10)–(2.13) was carried out by the well-known methods of parametric identification, based on the least squares methods using the REGRESS software package (A. Kuznetsov, B. Orazbaev, MISiS).

The results of the parametric identification of the models that determine the dependence of the yield of catalyzate from reactors, as well as the HCG yield on the operating parameters, have the form (2.15)–(2.18):

$$
\begin{aligned}
y_1^{R2} &= f_1(x_1, x_2, \ldots, x_5) = 0.398481x_1 + 12.153846154x_2 - \\
&-0.032113821x_3 - 0.983750x_4 + 0.01975000x_5 + \\
&+0.004937500x_1^2 + 9.349112426x_2^2 - 0.000065272x_3^2 - \\
&-0.037920000x_4^2 + 0.000049375x_5^2 + 0.227884615x_1x_2 + \\
&+0.000100356x_1x_3 + 0.001975000x_1x_4 + 0.000493750x_1x_5 + \\
&+0.037054409x_2x_3 - 0.486153846x_2x_4 - 0.000642276x_3x_4,
\end{aligned} \tag{2.15}
$$

$$
\begin{aligned}
y_1^{R3} &= f_1(x_1, x_2, \ldots, x_5) = 0.39500x_1 + 12.107692308x_2 - \\
&-0.031862348x_3 - 0.9837500x_4 + 0.019675000x_5 + \\
&+0.005044063x_1^2 + 9.313609467x_2^2 - 0.000064499x_3^2 - \\
&-0.040989583x_4^2 + 0.000049187x_5^2 + 0.229892892x_1x_2 + \\
&+0.000100830x_1x_3 + 0.002075422x_1x_4 + 0.000498101x_1x_5 + \\
&+0.036764248x_2x_3 - 0.504487179x_2x_4 - 0.000663799x_3x_4,
\end{aligned} \tag{2.16}
$$

$$
\begin{aligned}
y_1^{R4,\,40} &= f_1(x_1, x_2, \ldots, x_5) = 0.3989835x_1 + 12.0769231x_2 - \\
&-0.031589537 \times x_3 - 1.02391304 \times x_4 + 0.019625000x_5 + \\
&+0.005069676x_1^2 + 9.289940828x_2^2 - 0.000063560x_3^2 - \\
&-0.044517958x_4^2 + 0.000049063x_5^2 + 0.230182778x_1x_2 + \\
&+0.000100348x_1x_3 + 0.002168388x_1x_4 + 0.000498729x_1x_5 + \\
&+0.036449466x_2x_3 - 0.525083612x_2x_4 - 0.000686729x_3x_4,
\end{aligned} \tag{2.17}
$$

$$
\begin{aligned}
y_3 &= f_1(x_1, x_2, \ldots, x_5) = 500.0000x_1 + 7142.8571x_2 + 10.1010x_3 - \\
&-1458.3333x_4 + 25.0000x_5 + 6.2500x_1^2 + 5102.0408x_2^2 + \\
&+0.0204x_3^2 - 60.7639x_4^2 + 0.0625x_5^2 + 178.5714x_1x_2 + \\
&+0.2525x_1x_3 - 15.6250x_1x_4 + 15.6250x_1x_5 - 297.6190x_2x_4 - \\
&-2.5252x_3x_4 - 0.05051x_3x_5 - 1.0417x_4x_5.
\end{aligned} \tag{2.18}
$$

Fig. 2.6 shows a graph of the dependence of the yield of catalyzate with R-4, 4a on the reactor temperature.

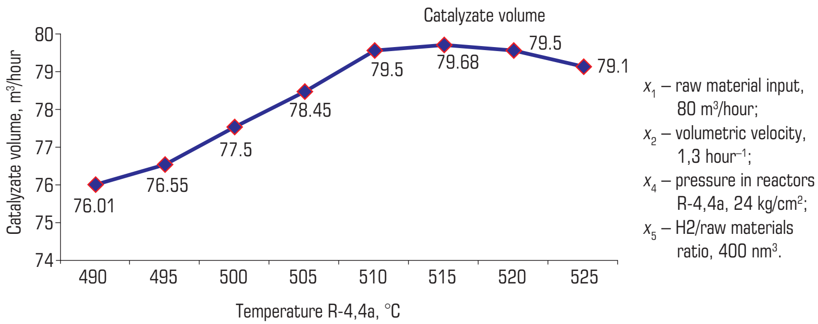


Fig. 2.6 Graph of dependence $y_1=f_1(x_3)$, x_1, x_2, x_4, x_5 – constants

To identify unknown fuzzy coefficients a_{ij}, $i=\overline{0,6}$ and $\tilde{a}_{ijk}$, $i,k=\overline{0,6}$, $j=\overline{4,8}$ in equations (2.10), the fuzzy sets describing the quality indicators of production are divided into the following sets of level α=0.5; 0, 0.75; 1. In accordance with the selected level, the values of the input x_{ij}, $i,j=\overline{4,8}$ and output $\tilde{y}_4,\tilde{y}_5,...,\tilde{y}_8$ parameters are observed at each level α_q $(q=\overline{1,3})$, which are presented in **Table 2.8**. This table shows the deterministic values of the input and output parameters at each selected level α_q.

For each level α_q of models of qualitative indicators of catalyzate (2.10), can be represented as a system of multiple regression equations [149], then the problem of identifying their coefficients $a_{ij}^{\alpha q}$ $(i=\overline{0,6},\ j=\overline{4,8},\ q=\overline{1,3})$ is reduced to the classical problems of estimating multiple regression parameters. To solve the latter problem, one can use well-known algorithms or standard multiple regression programs included in the computer software. The monograph uses the REGRESS software package used above.

The obtained values of the coefficients $a_{ij}^{\alpha_q}$, $i=\overline{0,6}$, $j=\overline{4,8}$, $q=\overline{1,3}$ of the model (2.14) are combined using the following relation:

$$\tilde{a}_{ij}=\underset{\alpha\in[0.5,1]}{\vee}a_{ij}^{\alpha_q}\ \text{or}\ \mu\tilde{a}_{ij}\left(a_{ij}\right)=\text{SUP}\min_{\alpha\in[0.5,1]}\left\{\alpha,\mu a_{ij}^{\alpha}\left(a_{ij}\right)\right\},$$

where $a_{ij}^{\alpha_q}=\left\{a_i \middle| \mu\tilde{a}_{ij}\left(a_{ij}\right)\geq\alpha\right\}$.

Thus, the mathematical models describing the fuzzy dependence of the quality parameters of the catalyzate $\left(\tilde{y}_j,\ j=\overline{4,8}\right)$ on the input parameters $(x_i,\ i=\overline{0,6})$ have the form:

$$\tilde{y}_4=\left(\frac{0.5}{0.430000}+\frac{0.75}{0.433000}+\frac{1}{0.435000}+\frac{0.75}{0.437000}+\frac{0.5}{0.440000}\right)x_{14}-$$

$$-\left(\frac{0.5}{20.076906}+\frac{0.75}{20.076916}+\frac{1}{20.076923}+\frac{0.75}{20.076930}+\frac{0.5}{20.076938}\right)x_{24}+$$

$$+\left(\frac{0.5}{0.052810}+\frac{0.75}{0.052824}+\frac{1}{0.052834}+\frac{0.75}{0.052844}+\frac{0.5}{0.052858}\right)x_{34}-$$

$$-\left(\frac{0.5}{0.724870}+\frac{0.75}{0.724950}+\frac{1}{0.720000}+\frac{0.75}{0.725050}+\frac{0.5}{0.725130}\right)x_{44}+$$

$$+\left(\frac{0.5}{0.042209}+\frac{0.75}{0.042339}+\frac{1}{0.042439}+\frac{0.75}{0.042539}+\frac{0.5}{0.042669}\right)x_{54}+$$

$$+\left(\frac{0.5}{0.005198}+\frac{0.75}{0.005328}+\frac{1}{0.005438}+\frac{0.75}{0.005548}+\frac{0.5}{0.005688}\right)x_{14}^2-$$

$$-\left(\frac{0.5}{15.443467}+\frac{0.75}{15.443637}+\frac{1}{15.446787}+\frac{0.75}{15.443937}+\frac{0.5}{15.443112}\right)x_{24}^2+$$

$$+\left(\frac{0.5}{0.000007}+\frac{0.75}{0.000057}+\frac{1}{0.000107}+\frac{0.75}{0.000157}+\frac{0.5}{0.000207}\right)x_{34}^2-$$

$$-\left(\frac{0.5}{0.030058}+\frac{0.75}{0.030138}+\frac{1}{0.030138}+\frac{0.75}{0.030278}+\frac{0.5}{0.030358}\right)x_{44}^2+$$

$$+\left(\frac{0.5}{0.000004}+\frac{0.75}{0.000054}+\frac{1}{0.000104}+\frac{0.75}{0.000154}+\frac{0.5}{0.000224}\right)x_{54}^2+$$

$$+\left(\frac{0.5}{0.000100}+\frac{0.75}{0.000170}+\frac{1}{0.000220}+\frac{0.75}{0.000270}+\frac{0.5}{0.000340}\right)x_{14}x_{34}+$$

$$+\left(\frac{0.5}{0.000125}+\frac{0.75}{0.000205}+\frac{1}{0.000265}+\frac{0.75}{0.000325}+\frac{0.5}{0.000405}\right)x_{14}x_{54}-$$

$$-\left(\frac{0.5}{0.557242}+\frac{0.75}{0.557492}+\frac{1}{0.557692}+\frac{0.75}{0.557892}+\frac{0.5}{0.558142}\right)x_{24}x_{44}+$$

$$+\left(\frac{0.5}{0.00006}+\frac{0.75}{0.000046}+\frac{1}{0.000086}+\frac{0.75}{0.000126}+\frac{0.5}{0.000166}\right)x_{34}x_{54};$$

$$\tilde{y}_5 = \left(\frac{0.5}{0.406050} + \frac{0.75}{0.406150} + \frac{1}{0.406250} + \frac{0.75}{0.406400} + \frac{0.5}{0.406600}\right) x_{15} -$$

$$-\left(\frac{0.5}{9.285214} + \frac{0.75}{9.285514} + \frac{1}{0.406250} + \frac{0.75}{9.285914} + \frac{0.5}{9.286214}\right) x_{25} +$$

$$+\left(\frac{0.5}{0.065793} + \frac{0.75}{0.065873} + \frac{1}{0.065923} + \frac{0.75}{0.065973} + \frac{0.5}{0.066053}\right) x_{35} -$$

$$-\left(\frac{0.5}{0.541417} + \frac{0.75}{0.541567} + \frac{1}{0.541667} + \frac{0.75}{0.541767} + \frac{0.5}{0.541917}\right) x_{45} -$$

$$-\left(\frac{0.5}{0.015849} + \frac{0.75}{0.015979} + \frac{1}{0.016049} + \frac{0.75}{0.016119} + \frac{0.5}{0.016249}\right) x_{55} +$$

$$+\left(\frac{0.5}{0.004978} + \frac{0.75}{0.005048} + \frac{1}{0.005108} + \frac{0.75}{0.005178} + \frac{0.5}{0.005078}\right) x_{15}^2 -$$

$$-\left(\frac{0.5}{6.6325961} + \frac{0.75}{6.6326331} + \frac{1}{6.6326531} + \frac{0.75}{6.6326731} + \frac{0.5}{6.6327101}\right) x_{25}^2 +$$

$$+\left(\frac{0.5}{0.000053} + \frac{0.75}{0.000103} + \frac{1}{0.000133} + \frac{0.75}{0.000163} + \frac{0.5}{0.000313}\right) x_{35}^2 -$$

$$-\left(\frac{0.5}{0.022179} + \frac{0.75}{0.022449} + \frac{1}{0.022569} + \frac{0.75}{0.022689} + \frac{0.5}{0.022959}\right) x_{45}^2 -$$

$$-\left(\frac{0.5}{0.000009} + \frac{0.75}{0.000029} + \frac{1}{0.000039} + \frac{0.75}{0.000049} + \frac{0.5}{0.000069}\right) x_{55}^2 +$$

$$+\left(\frac{0.5}{0.000428} + \frac{0.75}{0.000589} + \frac{1}{0.000659} + \frac{0.75}{0.000729} + \frac{0.5}{0.000878}\right) x_{15} x_{35} -$$

$$-\left(\frac{0.5}{0.386185} + \frac{0.75}{0.386655} + \frac{1}{0.386905} + \frac{0.75}{0.387155} + \frac{0.5}{0.387625}\right) x_{25} x_{45} -$$

$$-\left(\frac{0.5}{0.011015} + \frac{0.75}{0.011314} + \frac{1}{0.011464} + \frac{0.75}{0.011614} + \frac{0.5}{0.011915}\right) x_{25} x_{55} -$$

$$-\left(\frac{0.5}{0.000477} + \frac{0.75}{0.000599} + \frac{1}{0.000669} + \frac{0.75}{0.000739} + \frac{0.5}{0.000857}\right) x_{45} x_{55}.$$

Table 2.8 Deterministic values of the input and output parameters of the reforming reactor models at each selected level α_q

No.	Input, mode parameters										Output parameters							
	x_1 – volume of loading of raw material	x_2 – volumetric velocity in reactors	x_3^{R2} – temperature in reactor R-2	x_3^{R3} – temperature in reactor R-3	$x_3^{R4,\,4a}$ – temperature in reactors R-4, 4a	x_4^{R2} – pressure in reactor R-2	x_4^{R3} – pressure in reactor R-3	$x_4^{R4,\,4a}$ – pressure in reactors R-4, 4a	x_5 – H_2/raw material ratio	x_6 – temperature in furnace F-1	$y_1^{R_j}$ – volume of catalyzate from the reactor j	y_2 – dry gas volume	y_3 – HCG volume	y_4 – octane number of gasoline	y_5 – fractional composition 10 % dist.	y_6 – fractional composition 50 % dist.	y_7 – saturated vapor pressure	y_8 – content of actual resins
$\alpha=$**0.5**																		
1	68	1.3	490	500	503	33	29	27	400	515	67	930	100100	84–90	67.5–69.5	112-116	488–512	4.5–5.3
2	60	1.25	490	500	503	33	29	27	400	515	67	930	100100	84–90	67–70	112–116	485–515	4.5–5.3
3	68	1.3	477	500	503	33	29	27	400	515	67	930	100100	83–91	66–71	111–117	480–520	4.4–5.4
4	68	1.3	485	487	503	33	29	27	400	515	67	930	100100	84–90	65–72	110–118	475–525	4.3–5.5
5	68	1.3	490	500	494	33	29	27	400	515	67	930	100100	84–90	64–73	109–119	470–530	4.2–5.6
$\alpha=$**0.75**																		
1	68	1.3	490	500	503	33	29	27	400	515	67	930	100100	85–89	67–69	113–115	490–510	4.6–5.2
2	60	1.25	490	500	503	33	29	27	400	515	67	930	100100	85–89	67.5–69.5	113–115	490–510	4.6–5.2
3	68	1.3	477	500	503	33	29	27	400	515	67	930	100100	86–90	69–70	113.5–115.5	490–510	4.65–5.25
4	68	1.3	485	487	503	33	29	27	400	515	67	930	100100	85–89	69.5–70.5	114–116	490–510	4.7–5.3
5	68	1.3	490	500	494	33	29	27	400	515	67	930	100100	85–89	70–71	114.5–116.5	490–510	4.75–5.35
$\alpha=$**1.0**																		
1	68	1.3	490	500	503	33	29	27	400	515	67	930	100100	87	68	114	500	4.7
2	60	1.25	490	500	503	33	29	27	400	515	59	920	100000	87	68.5	114	500	4.7
3	68	1.3	477	500	503	33	29	27	400	515	61	930	100100	88	68.7	114.3	500	4.8
4	68	1.3	485	487	503	33	29	27	400	515	62	930	100100	87	69	114.5	500	4.9
5	68	1.3	490	500	494	33	29	27	400	515	63	930	100100	87	70	115	500	5

50 % distillation was determined similarly y_5 – $\tilde{y}_6$ and the saturated vapor pressure – $\tilde{y}_7$, and the content of actual tar in mg per 100 ml of gasoline – $\tilde{y}_8$ was identified as follows:

$$\begin{aligned}
&y_8 = f_8\left(x_{18}, x_{28},\ \ldots, x_{58}\right) = (0.5/0.0219700 + 0.75/0.0219900 + 1/0.0220000 +\\
&+0.75/0.0220100 + 0.5/0.0220300)x_{18} - (0.5/0.9427770 + 0.75/0.9428271+\\
&+1/0.9428571 + 0.75/0.9428871 + 0.5/0.9429170)x_{28} + (0.5/0.0026410 +\\
&+0.75/0.0026655 + 1/0.0026775 + 0.75/0.0026895 + 0.5/0.0027140)x_{38} -\\
&-(0.5/0.0366215 + 0.75/0.0366515 + 1/0.0366667 + 0.75/0.0366815 +\\
&+0.5/0.0367115)x_{48} + (0.5/0.0021190 + 0.75/0.0021363 + 1/0.0021463 +\\
&+0.75/0.0021563 + 0.5/0.0021730)x_{58} + (0.5/0.0003302 + 0.75/0.0003387 +\\
&+1/0.0003437 + 0.75/0.0003487 + 0.5/0.0003572)x_{18}^2 - 0.5/0.8979100 +\\
&+0.75/0.8979392 + 1/0.8979592 + 0.75/0.8979792 + 0.5/0.8980270)x_{28}^2 +\\
&+(0.5/0.0000002 + 0.75/0.0000042 + 1/0.0000072 + 0.75/0.0000102 +\\
&+0.5/0.0000142)x_{38}^2 - (0.5/0.0022265 + 0.75/0.0022717 + 1/0.0022917 +\\
&+0.75/0.0023117 + 0.5/0.0023565)x_{48}^2 + (0.5/0.0000005 + 0.75/0.0000048 +\\
&+1/0.0000078 + 0.75/0.0000108 + 0.5/0.0000145)x_{58}^2 + (0.5/0.0000045 +\\
&+0.75/0.0000173 + 1/0.0000223 + 0.75/0.0000273 + 0.5/0.0000405)x_{18}x_{38} +\\
&+(0.5/0.0000030 + 0.75/0.0000095 + 1/0.0000134 + 0.75/0.0000170 +\\
&+0.5/0.0000240)x_{18}x_{58} - (0.5/0.0392272 + 0.75/0.0392557 + 1/0.0392857 +\\
&+0.75/0.0393157 + 0.5/0.0393742)x_{28}x_{48} + (0.5/0.0000004 + 0.75/0.0000014 +\\
&+1/0.0000022 + 0.75/0.0000030 + 0.5/0.0000040)x_{38}x_{58}.
\end{aligned}$$

The influence of other operating parameters on the output parameters, including those on a multidimensional space, has been investigated.

Research and building of linguistic models of the catalytic reforming process. To determine the optimal temperature of the reforming process on the basis of the proposed above method for synthesizing the linguistic model, the logical rule of conditional inference and the knowledge base, a linguistic model was built that describes the effect of the temperature of the reforming reactor on the catalzate yield and stability. This model implements linguistic dependence:

«If T_R is low, then the output y_1 is low, the stability of y_2 is below normal,

if T_R is average, then $y_1$is average, y_2 is normal,

if T_R is high, then y_1 is above average, y_2 is above normal,

if T_R is very high, then y1 is below average, y_2 is below normal»,

where T_R – temperature of the reactor; y_1 – volume of catalyzate from the reactor; y_2 – stability of the catalyst.

On the basis of expert procedures and applying the analytical dependence proposed in [150], membership functions describing fuzzy sets are determined:

$$\mu_A(T) = \exp\left(\left|(T-485)^{0.5}\right|\right)$$ – low reactor temperature;

$$\mu_A(T) = \exp\left(\left|(T-495)^{0.5}\right|\right)$$ – average reactor temperature;

$$\mu_A(T) = \exp\left(\left|(T-520)^{0.6}\right|\right)$$ – high reactor temperature;

$$\mu_A(T) = \exp\left(\left|(T-545)^{0.7}\right|\right)$$ – very high reactor temperature;

$$\mu_B(y_1) = \exp\left(\left|(y_1-65)^{0.4}\right|\right)$$ – low yield of catalyzate;

$$\mu_B(y_1) = \exp\left(\left|(y_1-70)^{0.6}\right|\right)$$ – average yield of catalyzate;

$$\mu_B(y_1) = \exp\left(\left|(y_1-75)^{0.7}\right|\right)$$ – yield of catalyzate is above average;

$$\mu_B(y_1) = \exp\left(\left|(y_1-67)^{0.5}\right|\right)$$ – yield of catalyzate is below average;

$$\mu_B(y_2) = \exp\left(\left|(y_2-70)^{0.3}\right|\right)$$ – catalyst stability is below normal;

$$\mu_B(y_2) = \exp\left(\left|(y_2-90)^{0.5}\right|\right)$$ – catalyst stability is normal;

$$\mu_B(y_2) = \exp\left(\left|(y_2-95)^{0.7}\right|\right)$$ – catalyst stability is above the norm;

$$\mu_B(y_2) = \exp\left(\left|(y_2-90)^{0.5}\right|\right)$$ – catalyst stability is normal.

Applying the structure of the linguistic model (2.4) and modifying it in relation to our conditions, on the basis of the method for synthesizing the linguistic model developed above, the following linguistic model was obtained:

$$\begin{aligned}
&f\tilde{x} \in \tilde{A}(l),\ then\ \tilde{y}_1 \in \tilde{B}_1(l),\ \tilde{y}_2 \in \tilde{B}_2(bn),\\
&f\tilde{x} \in \tilde{A}(av),\ then\ \tilde{y}_1 \in \tilde{B}_1(av),\ \tilde{y}_2 \in \tilde{B}_2(n),\\
&f\tilde{x} \in \tilde{A}(h),\ then\ \tilde{y}_1 \in \tilde{B}_1(aa),\ \tilde{y}_2 \in \tilde{B}_2(an),\\
&f\tilde{x} \in \tilde{A}(vh),\ then\ \tilde{y}_1 \in \tilde{B}_1(ba),\ \tilde{y}_2 \in \tilde{B}_2(bn),
\end{aligned} \tag{2.19}$$

where *l, bn, av, n, h, aa, an, vh, ba* – fuzzy variables describing, respectively, the concepts of «low», «below normal», «average», «normal», «high», «above average», «above normal», «very high», «below average»; $\tilde{x}$, $\tilde{y}_1$, $\tilde{y}_2$ – linguistic input and output variables describing, respectively, the temperature of the reactor, the volume of the catalyzate and the stability of the catalyst; $\tilde{A}, \tilde{B}_j$, $j=1,\ 2$ – fuzzy subsets characterizing $\tilde{x}, \tilde{y}_j$, $j=1,\ 2$.

The results of the formalization of fuzzy mapping, determining the relationship between $\tilde{x}_i$ and $\tilde{y}_j - R_{ij}$, determining the qualitative values of the parameters of the object and their numerical values from the fuzzy set of solutions are given in below.

Fuzzy mappings R_{ij} that determine the relationship between linguistic variables $\tilde{x}$ and $\tilde{y}_j$, $j=\overline{1,m}$ that estimate the effect of temperature on the yield of catalyzate and catalyst stability are determined on the basis of formula (2.5a), and have the form:

$$\mu_{R_{ij}}^{p}\left(\tilde{x},\tilde{y}_j\right)=\min\left[\mu_{A_1}^{p}\left(\tilde{x}\right),\ \mu_{B_j}^{p}\left(\tilde{y}_j\right),\ j=\overline{1,2},\ p=\overline{1,4}\right]. \quad (2.20)$$

Performing the intersection operation over fuzzy sets $\tilde{A}$ and $\tilde{B}$ (membership functions $\mu_{A_1}^{p}\left(\tilde{x}\right)$ and $\mu_{B_j}^{p}\left(\tilde{y}_j\right)$, according to (2.20), let's obtain the values of the membership function of the fuzzy mapping $\left(\mu_{R_1}^{p}\left(\tilde{x},\tilde{y}_j\right)\right)$. In this case, the membership functions based on sharpened expressions in Section 2 have the form:

$$\mu_{A1}^{1}(x)=\exp\left(\left|(x-485)^{0.5}\right|\right) \text{ – low reactor temperature;}$$

$$\mu_{A1}^{2}(x)=\exp\left(\left|(x-495)^{0.5}\right|\right) \text{ – average reactor temperature;}$$

$$\mu_{A1}^{3}(x)=\exp\left(\left|(x-520)^{0.6}\right|\right) \text{ – high reactor temperature;}$$

$$\mu_{A1}^{4}(x)=\exp\left(\left|(x-545)^{0.7}\right|\right) \text{ – very high reactor temperature;}$$

$$\mu_{B1}^{1}(y_1)=\exp\left(\left|(y_1-65)^{0.4}\right|\right) \text{ – low yield of catalyzate;}$$

$$\mu_{B1}^{2}(y_1)=\exp\left(\left|(y_1-70)^{0.6}\right|\right) \text{ – average yield of catalyzate;}$$

$$\mu_{B1}^{3}(y_1)=\exp\left(\left|(y_1-75)^{0.7}\right|\right) \text{ – yield of catalyzate is above average;}$$

$$\mu_{B1}^{4}(y_1)=\exp\left(\left|(y_1-67)^{0.5}\right|\right) \text{ – yield of catalyzate is below average;}$$

$$\mu_{B2}^{1}(y_2)=\exp\left(\left|(y_2-70)^{0.3}\right|\right) \text{ – catalyst stability is below normal;}$$

$$\mu_{B2}^{2}(y_2)=\exp\left(\left|(y_2-90)^{0.5}\right|\right) \text{ – catalyst stability is normal;}$$

$$\mu_{B2}^{3}(y_2)=\exp\left(\left|(y_2-95)^{0.7}\right|\right) \text{ – catalyst stability is above the norm;}$$

$$\mu_{B2}^{4}(y_2)=\exp\left(\left|(y_2-90)^{0.5}\right|\right) \text{ – catalyst stability is normal.}$$

To determine the fuzzy values of the object's output parameters and select their numerical values from the fuzzy set of solutions, let's use the compositional inference rule – based on the maximin product of expressions and expressions (2.5b):

$$\mu^{p}_{B_j}\left(\tilde{y}^{*}_{j}\right)=\max_{x\in X}\left\{\min\left[\mu^{p}_{A_j}\left(\tilde{x}^{*}\right),\,\mu^{p}_{R_{ij}}\left(\tilde{x}^{*},\tilde{y}_{j}\right)\right]\right\}, \qquad (2.21)$$

where $\tilde{x}^{*}$ – measured (estimated by experts) values of the input variable – temperature, then the desired set, to which the current measured values of the variable belong, is determined from the condition: $\mu_{Ai}\left(\tilde{x}^{*}\right)=\max\left(\mu_{A1}\left(\tilde{x}\right)\right)$.

The predicted values of the output variables (fuzzy values) are defined in the form of the corresponding accessory functions. Specific numerical values of the output parameters $\tilde{y}_j^{**}, j=\overline{1,2}$ from the fuzzy set of solutions are determined from relation (2.5c), i.e. those values of the input parameter are selected for which the maximum of the membership function is achieved.

Similarly, let's identify the structure of a linguistic model describing the influence of the raw material rate on the quantity and quality (octane number) of the target product of the reforming unit – catalyzate, which describes the logical conclusion «*The higher the raw material rate, the lower the octane number and the higher the yield of catalyzate*».

$$f\tilde{x}\in\tilde{A}(h),\ then\ \tilde{y}_1\in\tilde{B}_1(h),\ \tilde{y}_2\in\tilde{B}_2(h),$$

$$f\tilde{x}\in\tilde{A}(av),\ then\ \tilde{y}_1\in\tilde{B}_1(av),\ \tilde{y}_2\in\tilde{B}_2(av),$$

$$f\tilde{x}\in\tilde{A}(h),\ then\ \tilde{y}_1\in\tilde{B}_1(h),\ \tilde{y}_2\in\tilde{B}_2(h), \qquad (2.22)$$

where *l, h, av* – fuzzy variables describing, respectively, the concepts «low», «high»; «average»; $\tilde{x}, \tilde{y}_1, \tilde{y}_2$ – linguistic input and output variables, respectively, raw material rate, octane number and volume of catalyzate.

Based on the results of research and processing of the results of expert procedures, the following structure of a linguistic model was obtained, which evaluates the effect of pressure in the reactor on the yield of catalyzate and HCG, on the temperature and on the service life of the catalyst.

$$f\tilde{x}\in\tilde{A}(l),\ then\ \tilde{y}_1\in\tilde{B}_1(h),\ \tilde{y}_2\in\tilde{B}_2(h),\ \tilde{y}_3\in\tilde{B}_3(l),$$

$$f\tilde{x}\in\tilde{A}(n),\ then\ \tilde{y}_1\in\tilde{B}_1(av),\ \tilde{y}_2\in\tilde{B}_2(av),\ \tilde{y}_3\in\tilde{B}_3(av),$$

$$f\tilde{x}\in\tilde{A}(h),\ then\ \tilde{y}_1\in\tilde{B}_1(l),\ \tilde{y}_2\in\tilde{B}_2(h),\ \tilde{y}_3\in\tilde{B}_3(aa), \qquad (2.23)$$

where *l, h, n, av* – fuzzy variables describing, respectively, the concepts «low», «high», «normal», «average»; $\tilde{x},\ \tilde{y}_1,\ \tilde{y}_2,\ \tilde{y}_3$ – linguistic input and output variables, respectively, pressure $\left(\tilde{x}\right)$, volume of catalyzate $\left(\tilde{y}_1\right)$, hydrogen $\left(\tilde{y}_2\right)$ and quality of catalyzate $\left(\tilde{y}_3\right)$; $\tilde{A},\ \tilde{B}_j,\ j=\overline{1,3}$ – fuzzy subsets characterizing.

Mathematical model of the reforming furnace F-1. The multi-chamber reforming furnace F-1 is designed to restore the temperature in the reaction zone to a temperature of 490–530 °C.

The main technological parameters of the furnace in question, which are regulated and affect the process, include:

– loading in m^3/hour (entrance and exit – 60–80);

– temperature in °C (at the inlet – 433–443, at the outlet – 500–530);

– pressure in kg/cm^2 (24–28).

As a result of the analysis of the available data and the study of the operating modes of these units (**Table 2.1**), experimental-statistical methods for building models were selected for the development of models of these units.

The mathematical description, which is the basis of the model, should reveal the relationship between the parameters of the thermal operation of the furnace. As part of the mathematical description of the thermal operation of the furnace, the following three groups of ratios can be distinguished:

1. Equations describing the processes of heat and mass transfer (equations of heat conduction, equations of radiant and convective heat transfer, heat balance equations, etc.).

2. Theoretical and empirical dependences (dependences of thermophysical characteristics of materials on temperature, temperature dependence of enthalpies of vapors and liquids, etc.).

3. Constrains on operating parameters, which are set in the form of equalities or inequalities (fuel consumption, load, etc.).

The main disadvantage of the previously existing methods for calculating furnaces is that they are focused on assessing only the integral characteristics of heat transfer, which do not exclude the case of pipe burnout. Recently, on the basis of theoretical research, a modelling method has been developed that makes it possible to evaluate the local characteristics of heat transfer.

Mathematically, the essence of zonal calculation methods is to replace the integral-differential equations describing heat transfer by an approximating finite system of algebraic equations, from the solution of which the energy characteristics of heat transfer are determined – temperatures and resulting flows of individual zones of the system. For this purpose, the furnace under consideration is divided into a finite number of surface and volume zones with uniform radiation properties. This approach provides a more accurate calculation result (with an increase in the number of zones), but it is complex and requires data that are usually difficult to obtain in industrial conditions. At the same time, in order to simulate the operation of industrial furnaces in an interactive mode and to obtain information promptly, it is necessary to have a fairly simple mathematical model. Therefore, in this work, the developed modelling algorithm is based on the analytical method of *N*. Belokon [151], based on the joint solution of the heat balance and heat transfer equations.

To calculate the output parameters of the furnace based on statistical and experimental data, regression equations are included in the model. At the same time, it was assumed that the form of the distribution law of random measurements ε_j is close to normal, i.e.: $M[\varepsilon_j]=0$, $D[\varepsilon_j]=G^2=\text{const}$, $j=\overline{1,m}$.

Then the structure of the regression models that determine the volume (y_1) and the temperature of the outlet flow (y_2) of the F-1 furnace has the form:

$$y_j = a_{0j} + a_{1j}x_1 + a_{2j}x_2 + a_{3j}x_3 + a_{4j}x_1^2 + a_{5j}x_2^2 + a_{6j}x_3^2 +$$
$$+a_{7j}x_1x_2 + a_{8j}x_1x_3 + a_{9j}x_2x_3 + \varepsilon_j,\ j = 1,2, \tag{2.24}$$

where $a_{ij}, i = \overline{0,9}; j = 1,2$ – regression coefficients identified by the least squares method; x_1, x_2, x_3 – independent control parameters, respectively, the input flow, temperature and pressure in the furnace.

As a result of processing the data of regime sheets and other statistical data by the methods of regression analysis and using the REGRESS program considered above, the parameters of the models (2.24) were identified:

$$y_1 = f_1(x_1, x_2, x_3) = 0.495553x_1 + 0.017727x_2 - 0.866667x_3 +$$
$$+0.006297x_1^2 + 0.000040x_2^2 - 0.032098x_3^2 + 0.000676x_1x_2 +$$
$$+0.000676x_1x_2 + 0.007342x_1x_3 - 0.000657x_2x_3; \tag{2.25}$$

$$y_2 = f_2(x_1, x_2, x_3) = 0.662420x_1 + 0.597701x_2 - 5.777778x_3 +$$
$$+0.008438x_1^2 + 0.001374x_2^2 - 0.213991x_3^2 + 0.004568x_1x_2 +$$
$$+0.000676x_1x_2 + 0.049068x_1x_3 - 0.004427x_2x_3. \tag{2.26}$$

Deterministic and statistical approaches can be used to simulate the operating modes of separators, heat exchangers and reforming filters [68, 71, 99, 152].

2.9 EVALUATION OF RELIABILITY AND COMPARISON OF MODELLING RESULTS

The developed mathematical models of the main units of the catalytic reforming unit of the LG-35-11/300-95 unit of the Atyrau refinery in accordance with the course of the process are combined into a single package. In the investigated unit of the unit, the outputs of the F-1 furnace models are the inputs for the reactor models, the output results of the R-2 model through the following F-1 sections enter the initial data for the P-3 reactor model. Further, the results of the R-3 simulation are used as input data for the models of the R-4, 4a reactors.

In accordance with this scheme, the developed models of the main units are combined into a single system. This system is a package of models, i.e. interconnected programs (F-1, R-2, R-3, R-4, 4a, R-7, R-9), according to the scheme according to which the results of the calculation of one program (model output) are the initial data for another program (model input). By simulating with the help of this package various modes of operation of the unit in a dialogue mode, one can select rational modes of operation of the object, solve optimization problems (according to algorithms that will be considered in the next section) and develop recommendations for controlling the process.

The reliability of the results, scientific statements and conclusions is confirmed by the correctness of the research methods used, based on the scientific principles of systems research and the theory of mathematical modelling, by the sufficient convergence of theoretical and experimental-industrial research results (relative error no more than 3 %).

The results of modelling the operation of the units and comparing them with the known data of other results, as well as experimental – production data of the plant are given in the form of tables (**Table 2.9**).

Table 2.9 Comparison of the results of the operation of known models [153], the proposed models and experimental data of the LG unit of the Atyrau refinery

Defined parameters	Known models [153]	Suggested models	Experimental data
Target product yield, % (mass)	94.8	95.3	95.0
Content of aromatic hydrocarbons Y_A, % (mass)	68.9	–	–
Catalyst volume, m^3/hour	77.2	77.8	77.5
The octane number of gasoline (catalyzate) by the motor method		87	(86)^I
Fractional composition of catalyzate, °C: 10 % distillation 50 % distillation	 – –	 67 110	 (68)^I (114)^I
Actual resin content in mg per 100 ml of gasoline	–	5	(5)^I

Note: the input and operating parameters of the process are taken approximately the same, ()^I means that they are obtained in a laboratory way.

The data presented in the table show the advantages of the proposed modelling method in comparison with the known ones, since the simulation results (calculated) coincide more accurately with the real (experimental) data, and on the basis of the obtained models it is possible to determine the quality indicators of products in a fuzzy environment that do not determined by traditional modelling methods. In addition, the proposed set of models makes it possible to carry out systemic modelling of interconnected units, which makes it possible to find the «bottleneck» of the technological complex.

The following **Fig. 2.7** shows the main indicators of the table in the form of a diagram.

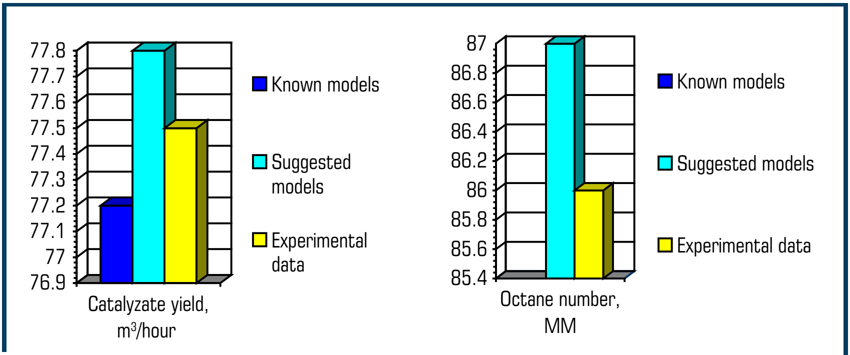


Fig. 2.7 Comparison of quantitative and qualitative indicators of hydrogenate

The data presented in the diagrams show that the use of the models developed in the work can increase the yield of catalyzate and improve its quality (the octane number increases). Moreover, the models are operable in a fuzzy environment, which made it possible to assess the quality of products.

2.10 CONCLUSIONS OF SECTION 2

1. As an effective means of formalizing fuzzy information and using it in developing models of complex, quantitatively difficult to describe objects and managing them in conditions of uncertainty, it is advisable to choose the methods of the theory of fuzzy sets. This is justified by the fact that the mathematical apparatus of the theory of fuzzy sets allows to formalize and use fuzzy information, which is the experience, knowledge and intuition of specialists, experts of the subject envelope. This approach to the formalization and use of fuzzy information in the modelling, optimization and management of complex objects makes it possible to take into account the intelligence of experts, taking into account the informalized connections between various parameters.

2. To reduce the lack of information in the study of production systems, arising from the random nature of the parameters, it is possible to use the methods of probability theory, and if the initial information is fuzzy, it is advisable to use the mathematical apparatus of the theory of fuzzy sets.

In the methods of expert assessments, when experts are quantitatively at a loss or cannot assess objects, a fuzzy approach should be applied. Based on the methods of the theory of possibilities, a new method of expert assessment is proposed, which allows organizing and conducting an expert survey in a fuzzy environment using high-quality information.

The method is presented in the form of a specific algorithm and is effectively implemented when conducting an expert assessment in order to collect the missing information about the operation of the reforming unit of the LG unit of the Atyrau refinery, which is necessary for the development of mathematical models of the main units of the unit.

3. The applied methodology of fuzzy modelling of production systems, which is based on the principle of decomposition, formalization and use of information of a different nature, makes it possible to build models of complex, indistinctly described models in conditions of uncertainty.

4. The proposed methods for synthesizing models based on fuzzy information are based on taking into account the fuzziness of the initial information and allows to develop a fuzzy and linguistic model depending on the fuzziness of the input and output parameters of the object. To solve the subtasks of the synthesis of fuzzy models related to the building of the membership function and interpolation of a set of terms, one should use methods based on human knowledge and experience and the theory of fuzzy sets.

5. An increase in the reliability of expert data can be achieved through an additional examination, according to the results of which the reliability of the information will be assessed, and measures to clarify it are applied.

6. The proposed method for creating a complex of models is based on building and combining various types (deterministic, statistical, fuzzy, combined) models of aggregates, taking into account the available information of a different nature (theoretical, statistical and fuzzy) into a single package. The proposed approach is implemented when building a package of models for the main units of the catalytic reforming unit of the LG unit.

7. A methodology for the development of mathematical models of interconnected technological units of the LG unit is proposed. Novelty, which consists in the application of a systematic approach, the use of fuzzy information and other available data, which allows solving the problems of uncertainty. The technique makes it possible to develop the most effective type of models for individual units of the technological system, create a package of models and carry out system modelling of the unit in order to determine the optimal modes of its operation. The practical significance of the research results is that the proposed method can be successfully applied in the development of mathematical models of various technological units of oil refining, petrochemistry and other industries.

8. Based on the results of research and processing of the collected quantitative and qualitative information, statistical and combined models of the R-1 hydrotreating and reforming reactors R-2, R-3, R-4, 4a, the F-101 hydrotreating furnace and the F-1 reforming furnace were built. On the basis of the proposed method of synthesis of the linguistic model, linguistic models have been formalized and identified, which describe:

– the effect of the temperature of the reforming reactor on the yield of catalyzate and the stability of the catalyst;

– the effect of the raw material rate on the quantity and quality (octane number) of the catalyzate;

– the influence of the pressure in the reactor on the yield of catalyzate and HCG, on the temperature and on the life of the catalyst.

The results of modelling the operation of the units of the reforming unit of the LG unit based on the proposed fuzzy approach are compared with the results of known methods and experimental – production data, the advantages of the proposed modelling methods are shown, which make it possible to effectively simulate a technological complex in a fuzzy environment.

3 STATEMENT OF DECISION-MAKING PROBLEMS FOR MANAGING THE TECHNOLOGICAL COMPLEX OF THE REFORMING UNIT AND DEVELOPMENT OF THE ALGORITHMS OF THEIR SOLUTION

ABSTRACT

In the section, mathematical formulations of decision-making problems for the control of the technological complex of the reforming unit are formalized and posed, and a set of heuristic algorithms for their solution is developed.

The novelty of the obtained multicriteria decision-making problems and algorithms for their solution using the initial fuzzy information lies in the fact that in them the problems are posed and solved in a fuzzy environment, without converting them to deterministic problems, i.e. preserving and using available information of a verbal nature. This approach, based on the knowledge and experience of expert specialists, makes it possible to obtain adequate solutions to complex production problems in a fuzzy environment. To solve the problems of multi-criteria, modified compromise schemes are used, adapted to work in a fuzzy environment. The formulation of the problem of decision-making on the control of the catalytic reforming unit is proposed on the basis of the developed mathematical models of the main units of this unit.

The developed heuristic algorithms for solving the assigned decision-making problems, which are based on the idea of various compromise schemes and their combination (methods of the main criterion (MC) and maximin (MM), the principles of Pareto optimality (PO) and ideal point (IP), absolute (relative) concessions) (A(R)C) and Pareto optimality). The applied compromise schemes are modified and adapted to work in a fuzzy environment. The proposed formulations of the problem and algorithms for their solution are a generalization of multicriteria problems in the case of indistinctness of the initial information; they are efficient in special cases when there is quantitative (crisp) information.

The correctness and performance of the proposed heuristic algorithms for solving decision-making problems are determined. The issues of convergence and stability of the solution are considered, and the effectiveness of the proposed heuristic algorithms is analyzed. These properties of the algorithms were confirmed when solving a specific problem of optimizing the operating modes of the reforming unit of the LG unit. The technique of choosing a specific algorithm from the developed system of algorithms for solving various DM problems is described, which depends on the production situation, on the available information and decision maker, as well as on the properties of the selected algorithms.

The results of solving the DM problem for the choice of optimal operating modes of the reforming unit of the LG unit of the Atyrau refinery using the proposed algorithm A(R)C+PO are presented.

KEYWORDS

Compromise schemes, problem of making decisions in a fuzzy environment, method of the main criterion, Pareto principle of optimality, maximin method, ideal point principle.

3.1 FORMALIZATION AND MATHEMATICAL FORMULATION OF DECISION-MAKING PROBLEMS FOR THE CONTROL OF THE CATALYTIC REFORMING UNIT BASED ON MATHEMATICAL MODELS

The results of the operation of production facilities are assessed by some indicators – local criteria of an economic, environmental, technological and other nature. For optimal control of such objects, it is required to convert these criteria to an extremum (maximum or minimum). Such problems are formalized in the form of multicriteria decision-making problems (DM), which are solved on the basis of mathematical models of the controlled object.

Due to the large number and variety of parameters that determine the course of catalytic reforming processes, due to internal relationships between the parameters of the technological complex, due to the mathematically non-formalized action of the human operator, these objects and their optimization are complex. In addition, when solving the problems of making decisions on the management of such objects, a number of problems often arise associated with a multitude of contradictory and indistinctly described criteria that determine the quality of the object's operation. In these cases, when solving DM problems, the main sources of information will be a person (experts, decision makers, technologist, block operator), i.e. its knowledge, experience, intuition and judgments, which are expressed by quality information, i.e. verbally.

Let's consider the approach to the formalization and formulation of DM problems in the conditions of the considered problems - multi-criteria and uncertainty caused by the fuzziness of the available information. Let's concretize the formalization and formulation of optimization problems based on mathematical models using the example of decision-making on the control of the technological complex of the catalytic reforming unit described in the previous section.

Let $f(x) = f_1(x),\ldots,f_m(x)$ vector of criteria assessing the quality of work, for example, the economic efficiency and environmental safety of the technological complex of the reforming unit. For example: $f_1(x)$, $f_2(x)$, $f_3(x)$ – respectively, the yield of the target product is the volume of catalyzate, dry gas and HCG (hydrocarbon containing gas); $f_4(x)$, $f_5(x)$,..., $f_{14}(x)$ – qualitative indicators of the output products (for example, for catalyzate – gasoline: octane number; fractional composition according to GOST 2177-82 – 10 % and 50 % distillation; saturated vapor pressure; content of actual resins, content of water-soluble acids and alkalis; for dry gas: content hydrogen, methane, ethane, propane, isobutane and *n*-butane; for HGC: hydrogen in % by volume; specific gravity), $f_{15}(x)$, $f_{16}(x)$,..., $f_{23}(x)$ – local criteria for assessing environmental safety, for example, solid, liquid and gaseous waste and emissions (spent catalysts, waste water emissions into the atmosphere – hydrocarbon gases, hydrogen sulfide, sulfurous anhydride, carbon monoxide, nitrogen dioxide, soot), as well as damage from environmental pollution by oil products and processing waste [136].

Each of the m criteria depends on the vector of *n* parameters (control actions, operating parameters) $x = (x_1,\ldots,x_n)$, for example: temperature and pressure of reactors, furnaces, etc.; composition of raw materials, characteristics of catalysts, etc. This dependence is described by the models developed in the previous section. In practice, there are always various constraints (economic, technological, environmental), which can be described by some functions – constraints

$\varphi_q(x) \geq b_q,\ q = \overline{1,L}$. It should be noted that some of the considered local criteria and constraints are reduced to qualitative constraints of the form no more or less than b_q ($\varphi_q(x) \tilde{\gtrless} b_q,\ q = \overline{1,L}$). Operating, control parameters also have their own intervals of change, set by the technological regulations of the unit: $x_i \in \Omega = \left[x_j^{\min}, x_j^{\max}\right], x_j^{\min},\ x_j^{\max}$ – the lower and upper limits of the parameter x_j. These limits may be fuzzy $\left(\tilde{>}, \tilde{<}, \tilde{=}\right)$.

It is required to choose the optimal solution – the mode of operation of the reforming unit, which ensures the extreme value of the criteria vector when the given constraints are met and some initial data are fuzzy, as well as taking into account the preferences of the decision maker.

A formalized task in conditions of multicriteria and fuzziness can be written in the form of the following DM problem:

$$\max_{x \in X} f_i(x),\ i = \overline{1,m}; \tag{3.1}$$

$$X = \left\{x \in \Omega, \varphi_q(x) > b_q, q = \overline{1,L}\right\}. \tag{3.2}$$

The solution to this problem is the value of the vector of operating parameters $x^* = \left(x_1^*, \ldots, x_n^*\right)$, which provides such values of local criteria that satisfy the decision maker.

If part or all of the elements of the given problem (criteria, constraints, the importance of criteria and constraints) are described not quantitatively, but qualitatively (indistinctly), then such a problem is called a DM problem under conditions of uncertainty based on qualitative information. In the known methods for solving such problems, mainly single-criterion cases are considered, there is no flexibility in taking into account the preferences of the decision maker. In this case, as a rule, a fuzzy problem at the stage of formulation is replaced by an equivalent deterministic one, which will lead to the loss of some information.

In many cases, qualitative factors (fuzzy statements and judgments) are basic and familiar to a person. Converting a fuzzy description into a quantitative one is not always successful or turns out to be impractical. In this regard, this paper proposes the most promising approach based on the development of DM methods adapted to the human language, to qualitative factors of any nature, to human decision-making procedures that are posed and solved in a fuzzy environment, without transforming them to deterministic problems, that is, without losing the available information of a fuzzy nature [149].

Thus, let's reduce problem (3.1), (3.2) to a multicriteria DM problem taking into account the qualitative nature of the initial information.

Let $\mu_0(x) = \left(\mu_0^1(x), \ldots, \mu_0^m(x)\right)$ be the normalized criteria vector – $f_i(x),\ i = \overline{1,m}$ evaluating the control criteria of the catalytic reforming unit. Let's suppose that for each fuzzy constraint $\varphi_q(x) \tilde{\geq} b_q,\ q = \overline{1,L}$, a membership function of its fulfillment ${}_q(x)$, $q = \overline{1,L}$ is built. Either a number of priorities for local criteria $I_k = \{1, \ldots, m\}$ and constraints $I_r = \{1, \ldots, L\}$ are known, or a weight vector reflecting the mutual importance of the criteria $\left(\gamma = \left(\gamma_1, \ldots, \gamma_m\right)\right)$ and constraints $\left(\beta = \left(\beta_1, \ldots, \beta_L\right)\right)$.

Then, for example, based on the idea of the *main criterion* and *maximin* methods, the multicriteria DM problem with vector constraints, taking into account the qualitative initial information (3.1), (3.2), can be written in the following formulation:

$$\max_{x \in X} \mu_0^1(x), \tag{3.3}$$

$$X = \left\{ x:\ x \in \Omega, \wedge \arg\left(\mu_0^i(x) \geq \wedge \mu_R^i\right) \wedge \left(\max_{x \in \Omega} \min_{q \in L} \left(\beta_q \mu_q(x) \right) \right),\ i = \overline{2,m},\ q = \overline{1,L} \right\}, \tag{3.4}$$

where $\wedge$ – logical sign «and», which requires that all the statements connected by it be true, μ_R^i – boundary values for local criteria $\mu_0^i(x)$, $i = \overline{2,m}$ set by the decision maker. The scope of the variables x and the fulfillment of fuzzy constraints is determined on the basis of the maximin principle (guaranteed result).

Changing μ_R^i and the constraint importance vector $\beta = (\beta_1, \dots, \beta_L)$, let's obtain a family of solutions to problem (3.3), (3.4): $x^*(\mu_R, \beta)$. The choice of the best solution can be carried out on the basis of a dialogue with the decision maker.

An algorithm for solving the obtained multicriteria optimization problem (3.3), (3.4) is developed and described in the next subsection.

Using the ideas of the *Pareto optimality* and *ideal point* methods, modifying them for the case of a qualitative nature of the initial information, the multicriteria DM problem (3.1), (3.2) can be rewritten as:

$$\max_{x \in X} \mu_0(x),\ \mu_0(x) = \sum_{i=1}^{m} \gamma_i \mu_0^i(x), \tag{3.5}$$

$$X = \left\{ x:\ x \in \Omega, \wedge \arg \mu_q(x) \geq \min \left\| \mu(x) - \mu^u \right\|_D,\ q = \overline{1,L} \right\}, \tag{3.6}$$

where $\| \cdot \|_D$ – used metric D, $\mu(x) = (\mu_1(x), \dots, \mu_L(x))$, $\mu^u = (\max \mu_1(x), \dots, \max \mu_L(x))$. A variant of using units as the coordinates of an ideal point μ^U is possible: $\mu^U = (1, \dots, 1)$; $\gamma = (\gamma_1, \dots, \gamma_m)$ – a weight vector reflecting the mutual importance of local criteria.

To solve the multicriteria problem with the DM formulation (3.5), (3.6), based on the modification of the used compromise schemes, an algorithm for its solution is proposed in the next section.

Using the idea of the principles of absolute (relative) concession and Pareto optimality under fuzzy conditions, it is possible to pose the following multicriteria DM problem with several constraints:

$$\max_{x \in X} \mu_0(x),\ \mu_0(x) = \sum_{i=1}^{m} \gamma_i \mu_0^i(x),\ \mu_0(x) = \prod_{i=1}^{m} \left(\mu_0^i(x) \right)^{\gamma_i}$$

or

$$\mu_0(x) = \sum_{i=1}^{m} \gamma_i \log \mu_0^i(x); \tag{3.7}$$

$$X = \left\{ x:\ x \in \Omega, \wedge \arg\max_{x\in\Omega} \sum_{q=1}^{L} \beta_q \mu_q(x) \wedge \sum_{q=1}^{L} \beta_q = 1 \wedge \beta_q \geq 0,\ q = \overline{1,L} \right\}, \tag{3.8}$$

sign «and», which requires that all the statements it connects to be true, $\gamma = (\gamma_1,\ldots,\gamma_m)$ and $\beta = (\beta_1,\ldots,\beta_L)$ – accordingly, the weight vectors reflecting the mutual importance of the criteria and constraints.

Thus, in this section, various DM problems are formalized for the optimal control of operating modes of a technological complex of oil refining using the example of a catalytic reforming unit under conditions of uncertainty. On the basis of compromise schemes and methods of the theory of possibilities, the tasks are posed in the form of multi-criteria DM problems, which are one of the novelty of research work. On the basis of these results, specific tasks for the adoption and selection of optimal operating modes of technological units of the catalytic reforming unit were obtained.

3.2 DEVELOPMENT OF HEURISTIC ALGORITHMS FOR SOLVING MULTI-CRITERIA DM PROBLEMS WHEN MANAGING A COMPLEX OF A REFORMING UNIT USING HIGH-QUALITY INFORMATION

In this subsection, let's propose a set of algorithms for solving problems of multicriteria problems of the DM formulation, which are obtained in subsection 3.1. The developed methods are based on the idea of various compromise schemes (methods of the main criterion and ideal point, Pareto principles of optimality, equality, etc.) of decision making, modified and workable on the basis of qualitative information (in a fuzzy environment).

To solve problem (3.3), (3.4), let's propose modified methods of the *main criterion* and *maximin*. Here the decision maker chooses (determines) the main criterion, which is optimized for the DM, and the remaining criteria are introduced into the system of constrains, preliminary, with the help of the decision maker, the boundary values of these criteria are determined. The degree of fulfillment of fuzzy constraints is taken into account using membership functions $\mu_q(x)$, $q = \overline{1,L}$, and the importance of each of the constraints is taken into account on the basis of the weight vector $\beta_q \geq 0$, $q = \overline{1,L}$ determined by the decision maker. The algorithm for solving the problem of the multicriteria DM problem (3.3), (3.4) based on this method consists of the following procedures:

MC+MM algorithm:

1. Set p_q, $q = \overline{1,L}$ – the number of steps for each q-th coordinate and a number of priorities for local criteria $I_k = \{1,\ \ldots, m\}$ (the main criterion must have priority 1).

2. Decision maker introduces the value of the weight vector of constrains $\beta = (\beta_1,\ldots,\beta_L)$, taking into account the importance of local constrains.

3. Decision maker is assigned boundary values (constrains) of local criteria μ_R^i, $i = \overline{2,m}$.

4. The steps for changing the coordinates of the weight vector $h_q = 1/p_q$, $q = \overline{1,L}$ are determined.

5. Building of a set of weight vectors $\beta^1, \beta^2, \ldots, \beta^N$, $N = (p_1+1)(p_2+1)(p_L+1)$, by varying coordinates on the segments [0, 1] with a step h_q.

6. The term-sets $T(X,Y)$, describing the qualitative (fuzzy) parameters of the object and the process, are determined.

7. The membership functions of the fulfillment of fuzzy constraints are built $\mu_q(x)$, $q=\overline{1,L}$.

8. The main criterion (3.3) is maximized on the set X, determined by the maximin principle (3.4), and the solutions $x^*(\mu_R^l,\beta),\mu_0^1(x^*(\mu_R^i,\beta)),...,\mu_0^m(x^*(\mu_R^i,\beta))$; $\mu_1(x^*(\mu_R^i,\beta)),...,\mu_L(x^*(\mu_R^i,\beta))$, $i=\overline{2,m}$ are found: The decision is presented by the decision maker. If the current results do not satisfy the decision maker, then new values μ_R^i, $i=\overline{2,m}$ are assigned to them and (or) the values of the weight vector of constrains are corrected, return to Step 3. Otherwise, go to Step 9.

9. The search for a solution is terminated, the results of the final choice of the decision maker are displayed: the values of the control vector $x^*(\mu_R^l,\beta)$; values of local criteria $\mu_0^1(x^*(\mu_R^i,\beta)),...,\mu_0^m(x^*(\mu_R^i,\beta))$; and degree of fulfillment of constraints $\mu_1(x^*(\mu_R^i,\beta)),...,\mu_L(x^*(\mu_R^i,\beta))$.

To solve the DM multicriteria problem (3.5), (3.6), the following method is proposed in this paper, developed on the basis of a modification of the *Pareto optimality and ideal point* compromise schemes [153]. Algorithmization of the developed method has the following structure:

PO+IP algorithm:

1. On the basis of expert judgment, determine the values of the weight vector, assessing the mutual importance of local criteria (objective functions) $\gamma=(\gamma_1,...,\gamma_m)$, $\gamma_i\geq 0$, $i=\overline{1,m}$, $\gamma_1+\gamma_2+...+\gamma_m=1$.

2. The term-sets $T(X,Y)$, describing the qualitative (fuzzy) parameters of the object and the process, are determined.

3. The membership functions of the fulfillment of fuzzy constraints are built $m_q(x)$, $q=\overline{1,L}$.

4. The coordinates of the ideal point are determined. The maximum values of the membership function: or units: $\mu^u=(1,...,1)$ (if the membership functions are normal) can be used as the coordinates of these points.

5. The form of the metric $\|\mu(x)-\mu^U\|_D$, is chosen, which determines the distance of the solution x^* from the ideal point – μ^U.

6. Solve problem (3.5), (3.6) and determine solutions: optimal values of control parameters – $x^*(g,\|\cdot\|_D)$; the values of local criteria $\mu_0^1(x^*(\gamma,\|\cdot\|_D))$, $\mu_0^2(x^*(\gamma,\|\cdot\|_D)),...,$ $\mu_0^m(x^*(\gamma,\|\cdot\|_D))$ and the degree of fulfillment of the constraints $\mu_1(x^*(\gamma,\|\cdot\|_D)),...,\mu_L(x^*(\gamma,\|\cdot\|_D))$.

7. Submit the decision to the decision maker. If the current results do not satisfy the decision maker, then they are assigned new values of the weight vector γ, and (or) a new type of metric $\|\cdot\|_D$ is selected and the search for an acceptable solution is repeated, otherwise the procedure for finding a solution is terminated and the final results are displayed.

To solve problem (3.7), (3.8), using and modifying the ideas of compromise schemes of absolute (relative) concession and Parato optimality, let's develop the following algorithm. The modified principle of absolute or relative concession is applied to the criteria, and the Pareto principle of optimality is applied to take into account the fulfillment of the constraints on the basis of the corresponding membership functions $\mu_q(x)$, $q=\overline{1,L}$. The heuristic algorithm for solving this optimization problem, implemented in the interactive mode, consists of the following main points.

A(R)C+PO algorithm:

1. Based on the expert procedure, the values of the weight vector $\gamma = (\gamma_1, \ldots, \gamma_m)$, $\sum_{i=1}^{m} \gamma_i = 1$, $\gamma_i \geq 0, i = \overline{1,m}$.

2. In case of ambiguity $\mu_0(x), \gamma$ for them, define term-sets and build membership functions.

3. The term-set is determined, describing quality parameters and restrictions.

4. The membership functions of the fulfillment of constraints $\mu_q(x)$, $q = \overline{1,L}$ are built.

5. The decision maker introduces the value of the weight vector of restrictions $\beta = (\beta_1, \ldots, \beta_L)$ taking into account the importance of local restrictions.

6. The problem of maximization $\max \mu_0(x)$,

$$\mu_0(x) = \sum_{i=1}^{m} \gamma_i \mu_0^i(x)$$

is solved (in the case of an absolute concession) or

$$\mu_0(x) = \prod_{i=1}^{m} \left(\mu_0^i(x)\right)^{\gamma_i}, \text{ or } \mu_0(x) = \sum_{i=1}^{m} \gamma_i \log \mu_0^i(x) \text{ (in the case of a relative concession).}$$

Solutions are determined: optimal values of operating parameters: $x^*(\gamma, \beta)$; optimal values of local criteria: $\mu_0^1(x^*(\gamma,\beta)), \ldots, \mu_0^m(x^*(\gamma,\beta))$ and the degree of fulfillment of the constraints $\mu_1(x^*(\gamma,\beta)), \ldots, \mu_L(x^*(\gamma,\beta))$.

7. The decision is presented to the decision maker. If the current results do not satisfy the decision maker, then they are assigned new values or the values γ and (or) β are corrected, and return to Step 2. Otherwise, go to Step 8.

8. The search for a solution is terminated, the results of the final choice of the decision maker are displayed: the values of the control vector $x^*(\gamma,\beta)$, the values of local criteria $\mu_0^1(x^*(\gamma,\beta)), \ldots, \mu_0^m(x^*(\gamma,\beta))$ and the degree of fulfillment of the constraints $\mu_1(x^*(\gamma,\beta)), \ldots, \mu_L(x^*(\gamma,\beta))$.

Thus, a set of dialog algorithms has been developed for solving multi-criteria DM problems for choosing the optimal operating modes of technological objects of oil refining production in conditions of uncertainty using the example of the technological complex of the catalytic reforming unit of the LG unit. The algorithms were obtained with the direct participation of the author of this monograph.

It should be noted that when solving the set tasks, it is possible to adapt and apply the algorithms proposed in [111, 112, 148], which are used to solve the problems of optimization and control of technological objects of other industries.

In the above formulations of the DM problems and the developed methods for their solution, the idea of preserving fuzziness was realized on the basis of the methods of compromise schemes, theories of fuzzy sets and possibilities. The proposed formulations of the problem and algorithms for their solution are a generalization of multicriterion problems in the case of indistinctness of the initial information; they are efficient in special cases when there is quantitative (crisp) information about the object under study, which ensures the universality of the approach.

3.3 INVESTIGATION OF THE PROPERTIES OF THE DEVELOPED HEURISTIC DECISION-MAKING ALGORITHMS AND A TECHNIQUE FOR CHOOSING THEM WHEN SOLVING SPECIFIC PRODUCTION PROBLEMS

Correctness and efficiency of algorithms. The correctness of the developed dialogue algorithms for solving optimization problems is primarily determined by the unambiguity of the information requested from the user. In this regard, the professional language used for dialogue between a person and a computer in the process of solving a problem should not contain synonyms and homonyms, which are a source of ambiguity in a strictly formalized language. Therefore, the user interface and dialog algorithms are designed with these requirements in mind, and, in general, it is necessary to use a regulated dialog in the form of a menu.

To overcome the problems of incorrectness caused by the indistinctness of the initial information, the term-set describing the problem is determined in advance, and the membership functions of the fuzzy parameters are built. In order to increase the adequacy of the membership function to indistinctly described categories, it is possible to use the method of building a non-belonging function and adjusting the parameters of the analytical dependence describing fuzzy parameters [150].

To establish the operability of the developed algorithms, it is necessary to draw up a program that implements the tested algorithm, and conduct a computational experiment, which will take into account various factors that affect the result of the algorithm. To assess the performance of the developed algorithms, they were tested in solving various production problems (test problems for making a decision when controlling the reforming unit). At the same time, the correspondence of the results obtained with real data and judgments of the decision maker, the time to achieve the final results, the convenience and ease of use of the algorithms under various production conditions were assessed.

The test results showed that the proposed algorithms meet the requirements of the decision maker and the imposed restrictions in all characteristics. Based on the results of a computational experiment, it is impossible to single out one algorithm that is the best in all indicators. Some algorithms are better in convergence (speed) (MC+MM algorithm), others in ease of use (PO+IP algorithm), some algorithms provide guaranteed results (MC+MM algorithms), others are more effective, but with a certain risk (algorithms PO+IP, A(R)C+PO), etc. In addition, the same algorithm may behave differently under different conditions and situations in production. In this regard, the decision maker is offered a set of algorithms, from which it chooses suitable ones, depending on the current situation and initial information.

The test results confirmed the efficiency and effectiveness of the proposed algorithms. It should be emphasized that for the algorithms being tested, a special selection of parameters and users was not carried out - decision makers or user training in order to improve the results. Comparative characteristics of the tested algorithms are shown in **Table 3.1**. The developed algorithms for multi-criteria fuzzy optimization and the development of mathematical models of the technological complex of oil refining are successfully used in the educational and scientific process of the Atyrau Institute of Oil and Gas.

Table 3.1 shows the average values of the obtained characteristics.

Table 3.1 Comparative characteristics of the proposed algorithms when solving test (production) problems

No.	Algorithms	Trade-off schemes and optimality principles used	Necessary information	Convergence in [sec]	Values of local criteria and its MF	Degree of fulfillment of constraints (MF)	Evaluation of usability [in points 1–5]
1	MC+MM algorithm	Main criterion + Maximin principle	The main criterion, the priority series $I_k=\{1,\dots,m\}$, the weight vector of constraints $\beta=(\beta_1,\dots,\beta_L)$, the boundary values of the criteria μ_r^i, $i=\overline{2,m}$. p_q, $q=\overline{1,L}$ – the number of steps along each q-th coordinate	80	72.5, $\mu_0^1(x^*(\mu_r^i,\beta))=0.98$	$\mu_1(x^*(\mu_r^i,\beta))=1$, $\mu_2(x^*(\mu_r^i,\beta))=0.99$, $\mu_3(x^*(\mu_r^i,\beta))=0.98$	4
2	PO+IP algorithm	Pareto Optimality + Ideal Point	Weight vector of criteria $\gamma=(\gamma_1,\dots,\gamma_m)$, coordinates of an ideal point, type of metric $\|\mu(x)-\mu^U\|_D$	90	70, $\mu_0^1(x^*(\mu_R^i,\ \|\cdot\|_D))=0.98$	$\mu_1(x^*(\mu_R^i,\ \|\cdot\|_D))=1$, $\mu_2(x^*(\mu_R^i,\ \|\cdot\|_D))=0.99$, $\mu_3(x^*(\mu_R^i,\ \|\cdot\|_D))=0.97$	5
3	A(R)C+PO algorithm	Absolute (relative) concession + Pareto optimality	$\beta=(\beta_1,\dots,\beta_L)$. Weight vector of criteria $\gamma=(\gamma_1,\dots,\gamma_m)$,weight vector of constraints	95	71, $\mu_0^1(x^*(\gamma,\beta))=0.98$	$\mu_1(x^*(\gamma,\beta))=1$, $\mu_1(x^*(\gamma,\beta))=1$, $\mu_1(x^*(\gamma,\beta))=1$	3

Note: MF – membership function; As test problems, various versions of the DM problem for controlling the reforming unit, solved in Section 3 (3.3), are considered.

Algorithm convergence and solution stability. Analysis of the effectiveness of algorithms. The convergence of algorithms for solving DM problems is determined by the time required to obtain results that satisfy the decision maker. Obviously, this time depends on subjective factors (knowledge, experience, reaction, working conditions, mood, readiness of users), on the structure of the interface, on the amount and content of information required from the decision maker, on the structure of algorithms and their software implementation, on the dimension of the problem and on the characteristics of the computer (performance, speed, etc.).

Therefore, to analyze and compare the performance of various algorithms, it is necessary to carry out tests (computational experiment) under the same conditions. The user (researcher) must be the same person who uses the same computer to solve the problem. According to the results of the computational experiment, it can be concluded that the most rapidly converging algorithms include the MC-MM algorithm, using the principles of the main criterion and maximin, and the slowest – the A(R)C-PO algorithm, using the principles of absolute (relative) concession and Pareto optimality.

To determine the stability of the solution, the developed algorithms were tested several times (5 – 6 times) when solving test production problems. Each time, the main characteristics of the algorithms and the results obtained were compared. The main source of interference (disturbances) in these tests can be attributed to the person – the user of the system. It should be noted that the results of these tests confirmed the stability of the developed algorithms. Almost the same results were obtained each time under the same test conditions.

The efficiency of the developed algorithms can be understood as the degree of their functional perfection, which is determined by a number of indicators, for example, speed, convergence, accuracy, noise immunity of algorithms, the economic effect obtained from their introduction into production, etc.

The main component of the generalized efficiency criterion is the value of the economic efficiency obtained as a result of the implementation of the algorithm in production. The results of pilot tests of the DM algorithms used to optimize the operating modes of the catalytic reforming unit have shown their high efficiency.

Summing up the results of testing and analyzing algorithms for solving various problems, it can be noted that the effectiveness of the developed algorithms varies depending on the initial information, on the dimension of the problem and on the user.

The most stable in various situations was the MC-MM algorithm based on the principles of the main criterion and maximin. With an increase in the dimension of the problem, the efficiency of algorithms PO+IP, A(R)C+PO decreases. This can be explained by the fact that with an increase in the dimension of the problem, the set of effective solutions increases, from which the decision maker must choose the final one.

Let's consider the principle of choosing a specific algorithm from the developed system of algorithms (MC+MM, PO+IP, A(R)C+PO) when solving DM problems for choosing the optimal operating modes of technological units.

The choice of a specific algorithm from the proposed system of algorithms for solving various optimization problems is carried out by the decision maker, depending on the available information, situations in production, the production plan – an order, the state of the object, the statement of the problem or at its discretion.

For example, if the problem can be reduced to maximizing one (main) criterion, and the remaining local criteria – to a constraint, then an algorithm is selected that uses the idea of the main criterion method – MC+MM. It should be noted that this algorithm is effectively used if it is possible to select a decision maker from the vector of the main criteria and, if necessary, to ensure a guaranteed result in fulfilling the constraints. If there is not a very large number of criteria (up to 5–7), when the decision maker, based on its preferences, can choose the best solution from a set of effective solutions, the ideal values of the constraints are determined, as well as the appropriate type of metric that estimates the distance between the current and ideal values of these indicators, then the PO+IP algorithm is selected, using the principles of Pareto optimality and the idea of the ideal point principle.

If it is necessary to introduce some concessions, taking into account the criteria and a small number of restrictions, the most suitable algorithms are A(R)C+PO, using the idea of absolute (relative) concession and Pareto optimality.

It is possible to set new DM problems by exchanging the places of the used principles for the criteria and constraints and to develop appropriate algorithms for their solution. It is possible to obtain new problems based on modification and other trade-off decision-making schemes for the case of fuzziness, i.e. expanding their areas of operation and develop methods for their solution.

3.4 FORMULATION AND SOLUTION OF THE DM PROBLEM TO OPTIMIZE THE OPERATING MODES OF THE CATALYTIC REFORMING UNIT

As an example, let's formulate and present solutions to the problem of making a decision to optimize the operating mode of the technological complex of the reforming unit of the LG unit of the Atyrau refinery. Any production that produces certain products (in our case, oil products) will be characterized by two parameters: the volume of products and their quality. The volume of output can be determined by various indicators: gross, sold, net standard production, etc. In our case, the volume of production (catalyzate) is measured in units of m^3/hour [64–80]. When it comes to assessing quality, things are not so simple here. It is very difficult and not always possible to assess the quality of products by one number. In this problem, the quality of the catalyzate is determined by:

– octane number (at least 86 according to the motor method);

– fractional composition – 10 % and 50 % distillation (respectively, not higher than 70 and 115 °C); saturated vapor pressure (no more than 500 mm Hg);

– actual resin content in mg per 100 ml of gasoline (not more than 5.0).

In fact, qualitative indicators are characterized by criteria or constraints such as «not less» and «not more», i.e. are fuzzy.

In practice, it is necessary to the release to be larger and the quality better. But, as it is known, these criteria are often contradictory and it is often impossible to improve them at the same time. The challenge is to find the optimal compromise solution, depending on the production situation and plan, as well as satisfying the decision maker.

Thus, using the above formulations of the DM problems to optimize the reforming process, it can be formalized and posed as follows:

Let $f(x)=F(f(x))=\mu_0^1(x)$ be a normalized criterion evaluating the yield of catalyzate. Let's assume that for each fuzzy constraint describing the quality indicators of production $\varphi_q(x)\tilde{\geq} b_q$, $q=\overline{1,5}$, a membership function of its fulfillment $\mu_q(x)$, $q=\overline{1,5}$ is built. Either a number of priorities for constraints $I_r=\{1,\ldots,3\}$ are known, or a weight vector reflecting the mutual importance of these constraints $\beta=(\beta_1,\beta_2,\beta_3)$.

As already noted, the criterion and constraints depend on the vector of parameters x_i, $i=\overline{1,5}$ (x_1 – raw material loading; x_2, x_3 – temperature and pressure in the reactors R-4, 4a; x_4 – volumetric raw material rate of the raw material; x_5 – hydrogen/raw material ratio). These dependencies describe the models developed in the previous section.

A formalized problem, under conditions of multicriteria and fuzziness, can be written similarly to (3.7), (3.8) in the form of the following DM problem:

$$\max_{x\in X}\mu_0(x), \tag{3.9}$$

$$X=\left\{x: x\in\Omega,\wedge \arg\max_{x\in\Omega}\sum_{q=1}^{5}\beta_q\mu_q(x)\wedge\sum_{q=1}^{5}\beta_q=1\wedge\beta_q\geq 0,\ q=\overline{1,5}\right\}. \tag{3.10}$$

The solution to this problem is the value of the vector of operating parameters $x^*=(x_1^*,\ldots,x_5^*)$, which ensures the optimal value of the criterion when the specified constraints are met, taking into account the preferences of the decision maker and satisfying it.

To solve the problem (3.9), (3.10), let's apply a simplified modification of the A(R)C+PO algorithm for the case of one criterion:

1. Since in our case there is one criterion, its weight is equal to 1, there is no need to determine the value of the weight vector $\gamma=(\gamma_1,\ldots,\gamma_m)$.

2. In the task $\mu_0(x)$, clearly, therefore, $T(X,Y)$ and membership functions are not built for it.

3. The term-set is determined, describing fuzzy restrictions. As a result of expert procedures, decision makers, expert experts to describe the limitation, the following were selected: at least 86 by the motor method; not higher than 70 °C; not higher than 115 °C; no more than 500 mm Hg; no more than 5.0 and their derivatives, which are obtained using various modifiers.

4. The membership functions of the fulfillment of constraints $\mu_q(x)$, $q=\overline{1,5}$ are built.

Based on the research results, the following membership functions of the fulfillment of the constraints are built:

$$\mu_1(x)=\exp\left(83.0\left|(y_2-87)^{0.78}\right|\right);$$

$$\mu_2(x)=\exp\left(75.0\left|(y_3-69)^{0.85}\right|\right);$$

$$\mu_3(x)=\exp\left(120.0\left|(y_4-114)^{0.50}\right|\right);$$

$$\mu_2(x)=\exp\left(510.0\left|(y_5-500)^{0.25}\right|\right);$$

$$\mu_3(x)=\exp\left(6.50\left|(y_6-5)^{1.5}\right|\right),$$

where y_2, y_3, y_4, y_5, y_6 – numerical values of the fuzzy indicators of the quality of the catalyzate obtained using the set of level a in Section 2; 1 – the coefficients determine the parameter that is found when identifying the membership function and that determines the level of fuzziness at the level of the parameter that is found when identifying the membership function and that determines the level of fuzziness at $\alpha=0.5$; 2 – the coefficients determine the fuzzy variable that most corresponds to the selected term, for which the membership function takes the maximum value (usually 1); 3 – the coefficients are used to change the domain of definition of terms and the shape of the graph of the membership function of fuzzy parameters.

5. The decision maker introduces the value of the weight vector of restrictions $\beta=(\beta_1,\dots,\beta_5)$, taking into account the importance of local restrictions. In our problem, the decision maker entered the following values $\beta_1=0.7$, $\beta_2=\beta_3=0.1$, $\beta_4=\beta_5=0.05$, i.e. $\beta=(0.7, 0.1, 0.1, 0.05, 0.05)$.

6. The problem of maximizing the criterion is solved, i.e. yield of catalyzate $\max\mu_0(x)$ taking into account the imposed fuzzy restrictions. The following solutions are determined: optimal values of operating parameters – $x^*(\beta)$; the optimal value of the criterion – $\mu_0(x^*(\beta))$ and the degree of fulfillment of the constraints – $\mu_1(x^*(\beta)),\dots,\mu_5(x^*(\beta))$.

7. The decision is presented to the decision maker. If the current results do not satisfy the decision maker, then new values are assigned to them or the values β are corrected, and return to Step 2. Otherwise, go to Step 8.

8. The search for a solution stops, the results of the final choice of the decision maker are displayed: the values of the control vector $x^*(\beta)$; the value of the criterion $\mu_0(x^*(\beta))$ and the degree of fulfillment of the restrictions $\mu_1(x^*(\beta)),\dots,\mu_5(x^*(\beta))$. These results are summarized in **Table 3.2**.

Table 3.2 Comparison of optimization results according to the proposed algorithm, according to the deterministic method [153] and experimental data

Values of criteria and constraints	**Deterministic method (literary data)**	**Proposed algorithm A(R)C+PO**	**Experimental data (Atyrau refinery)**
Catalyzate yield – criterion y_1, m^3/h	77.0	79.0	78.5
Octane number of products, MM (2) $(\tilde{y}_2)$	86	87	$(86)^{l}$
Fractional composition of catalyzate; 10 % distillation, °C $(\tilde{y}_3)$; 50 % distillation, °C $(\tilde{y}_4)$	 70 115	 70 114	 $(70)^{l}$ $(114)^{l}$
Saturated vapor pressure, mm Hg $(\tilde{y}_5)$	500	500	$(500)^{l}$
Actual resin content in mg. per 100 m $(\tilde{y}_6)$	5.0	4.8	$(5.0)^{l}$
The membership function of the fulfillment of the constraint $y_2 - \mu_1(x^*(\beta))$	–	1.0	–
The membership function of the fulfillment of the constraint $y_3 - \mu_2(x^*(\beta))$	–	1.0	–
The membership function of the fulfillment of the constraint $y_4 - \mu_3(x^*(\beta))$	–	0.97	–
The membership function of the fulfillment of the constraint $y_5 - \mu_4(x^*(\beta))$	–	0.98	–
The membership function of the fulfillment of the constraint $y_6 - \mu_5(x^*(\beta))$	–	1.0	–
Optimal values of input and operating parameters $x^*=(x_1^*,\dots,x_5^*)$: x_1^* – loading of raw materials, m^3/h	 80	 80	 80
x_2^* – volumetric velocity in the reactors, h^{-1}	1.7	1.3	1.5
x_3^* – temperature in reactors R-4, 4a, °C	500	493	495
x_4^* – pressure in reactors R-4, 4a, kg/cm^2	26	25	25
x_5^* – hydrogen/hydrocarbons ratio	415	400	400

Note: $()^{l}$ means that the corresponding quality indicators are determined by laboratory methods and require sufficient time; (–) means that the corresponding indicators are not determined by this method. The search time for a solution in the compared methods is almost the same: about one minute, taking into account the time of entering or correcting the required data.

Analysis of the results given in **Table 3.2** data gives grounds to draw the following conclusions:

1. The proposed algorithm is more efficient than the deterministic method.

2. When solving DM problems on the basis of the proposed algorithm, the adequacy of solving the production problem increases, since additional qualitative information (experience, knowledge of decision makers, expert specialists) is taken into account, which more fully describes the real situation without idealization.

3. The proposed and used algorithm makes it possible to determine the degree (function) of membership of a particular fuzzy constraint, i.e. the degree of correctness of the solutions obtained. The reliability of the results and conclusions obtained is confirmed by: the correctness of the research methods used, based on the scientific provisions of the optimization theory, theories of fuzzy sets and methods of expert assessments; sufficient convergence of the computational-model (theoretical) and experimental (pilot-industrial) research results (relative error no more than 3 %).

3.5 CONCLUSIONS OF SECTION 3

1. To formalize the DM problem for choosing the optimal operating modes of oil refining technological objects, such as the catalytic reforming unit of the LG unit, characterized by the indistinctness of the initial information, it is reasonable to use a heuristic approach that allows using the creative thinking of experts, experienced specialists in the subject area. The novelty of the received multicriteria DM problems based on qualitative information from expert specialists lies in the fact that tasks in them are set and solved in a fuzzy environment, without converting them to deterministic tasks, that is, preserving and using available information of a qualitative nature. This approach, based on the knowledge and experience of expert specialists, makes it possible to obtain adequate solutions to complex production problems. To solve the problems of multicriteria, one can use the ideas of compromise schemes and principles of optimality, pre-modifying them for the case of indistinctness of the initial information.

2. A set of dialogue algorithms for solving the assigned DM problems has been developed, which are based on the idea of various compromise schemes – the principles of optimality and their combination (methods of the main criterion (MC) and maximin (MM), the principles of Pareto optimality (PO) and ideal point (IP), absolute (relative) concessions (A(R)C) and Pareto optimality), the applied compromise schemes are modified and adapted to work in a fuzzy environment.

The proposed formulations of the problem and algorithms for their solution are a generalization of multicriteria problems for the case of a qualitative nature (fuzziness) of the initial information; they are efficient in special cases when there is quantitative (crisp) information.

3. The properties of the developed optimization algorithms are investigated. The correctness and efficiency of the proposed algorithms when solving the assigned tasks largely depends on the quality of the formalization of fuzzy information.

The issues of convergence and stability of the solution are considered, and the effectiveness of the proposed algorithms is analyzed. These properties of the algorithms were confirmed when solving a specific problem of optimizing the operating modes of the reforming unit of the LG unit. A specific algorithm from the developed system of algorithms for solving various DM problems must be selected depending on the production situation, on the available information and decision maker, as well as on the properties of the selected algorithms.

4. On the basis of the A(R)C+PO algorithm, the DM problem of the optimal operating modes of the reforming unit of the LG unit of the Atyrau refinery was solved. The comparison of the results of solving DM problems on optimization according to the proposed algorithm, according to the deterministic method and experimental data shows the effectiveness of the proposed method for solving multi-criteria DM problems in a fuzzy environment.

4 CREATION AND RESEARCH OF A MODELLING AND DECISION-MAKING SYSTEM

ABSTRACT

Based on the results of the research carried out, the built mathematical models and algorithms for solving decision-making problems, a computer system for modelling and decision-making is being created for choosing the optimal operating modes of the research object. The analysis of the problems of modelling and decision-making in the management of production facilities is carried out.

The architecture of a computer modelling and decision-making system is created for the selection of optimal operating modes of a technological object and a methodology for the development of functional blocks of such a system is proposed. The advantages of the proposed computer system for modelling and decision-making over similar systems are that it includes a package of mathematical models of the investigated object, developed using fuzzy information, a set of algorithms for solving multicriteria decision-making problems in a fuzzy environment based on the knowledge, experience and intuition of the decision maker, professional experts, as well as an intelligent interface. The prospects for the application of the obtained research results are shown.

The main results of the software implementation of the developed models are given and the description of the interface of the system for modelling the units of the reforming unit is given.

KEYWORDS

Computer system for modelling and decision making, intellectualized system, user interface, knowledge and data base, model parameter identifier.

4.1 PROBLEMS OF MODELLING AND DECISION-MAKING IN THE MANAGEMENT OF PRODUCTION FACILITIES

Determination of the quality of functioning of technological objects of any production, incl. oil refining, determination of optimal operating parameters, selection of an effective structure and algorithms of behavior, in accordance with the set goal – the main problems in the management of functioning facilities and the design of modern production.

Multicomponent, large dimension, multi-parameter and uncertainty in production conditions complicate the solution of these problems. Mathematical modelling and decision making methods are scientifically based effective approaches to solving these complex production problems. However, when applying modelling methods and making decisions in the process of production management, certain problems of a scientific and practical nature arise. Let's consider these problems and approaches to solving them.

Methods of mathematical modelling in combination with modern computational tools allow with high accuracy to quickly investigate various options for the functioning of a production system, study its main features and reveal reserves for improvement. In mathematical modelling, the process is investigated by changing various parameters connected in the form of a mathematical model on a computer. This allows to quickly obtain information about various variants of the studied process and determine the optimal conditions for the flow of technological and production processes, control it based on a mathematical model and transfer the results to the object.

Any kind of modelling is based on a certain *model* that has a correspondence based on some general quality that characterizes a real object. An objectively real object has a certain formal structure, therefore, any model is characterized by the presence of some structure corresponding to the formal structure of the real object, or the side of this object being studied.

In a production environment, complex organizational and technical systems, which can be classified as large systems, act as the object of modelling. Moreover, in terms of its content, the created model M also becomes a system $S(M)$ and can also be attributed to the class of large systems.

One of the most important aspects of building modelling systems is the goal problem. Any model is built depending on the goal that the researcher sets for it; therefore, one of the main problems in modelling is the problem of purpose. The similarity of the process proceeding in the model M to the real process is not a goal, but a condition for the correct functioning of the model, and therefore the goal should be the task of studying any aspect of the object's operation.

If the purpose of modelling is clear, then the following problem arises, namely, the problem of building a model M. The building of a model is possible if there is information or hypotheses are put forward regarding the structure, algorithms and parameters of the object under study. Based on their study, the identification of the object is carried out. Currently, various methods of parameter estimation are widely used (least squares method, maximum likelihood method, Bayesian, Markov estimates, etc.).

When building a model of production facilities, there are problems of information deficiency, uncertainty and fuzziness of the initial information. To solve the problems of uncertainty caused by the random nature of the parameters of the modeled object, probabilistic methods are used. It should be noted that these methods are applicable only under certain conditions – when the axioms of the probability theory are fulfilled (statistical stability of an object, multiple reproducibility of experimental results under the same conditions).

A feature of most production facilities and oil refining processes in which a person participates is their complexity, caused not only by a significant number and variety of parameters, but also by the unformalized action of a person participating in the control loop. In these conditions, in the study of objects and the building of their mathematical models, the problem of uncertainty associated with fuzziness arises – the qualitative nature of the initial information that can actually be collected for modelling the object under study. This problem is associated with the fact that usually complex objects are difficult to describe quantitatively, and special means for collecting and processing the necessary statistical data in an industrial environment are insufficient, do not have the necessary properties, or are absent. In these situations, often the only source of information is a person (production personnel, expert) who can formalize its knowledge, experience, intuition (information) in natural language (verbally) in the form of judgments, logical inference, i.e. the information collected is of a qualitative nature.

Attempts to extend traditional modelling methods to quantitatively difficult to describe objects (oil refining process plants) have not yet yielded good results, despite the significant development of mathematical methods, as well as computer technology. In practice, such objects and processes are managed quite well by a person (operator-technologist, manager). In such cases, a person quite successfully copes with the uncertainty and complexity of the management process.

Unlike a machine, a person uses fuzzy qualitative concepts and is quite successful in navigating difficult situations. In this regard, the problem arises of how to transfer human abilities to a machine for modelling and managing complex industrial objects and production processes. To solve such a problem, special methods of fuzziness formalization and processing of fuzzy, high-quality information are required. Of the various methods for solving these problems, the methods of the theories of fuzzy sets and possibilities, which are used in combination by the methods of expert assessments, can be distinguished as the most effective. It is these methods that are applied and developed in this research work in the development of models and decision-making on the management of technological facilities of oil refining on the example of the reforming unit of the LG unit of the Atyrau refinery.

If the model M is built, then the next problem can be considered the problem of working with it, i.e. implementation of the model, the main tasks of which are minimization of the time to obtain the final results and ensuring their reliability. For a correctly built model M, it is characteristic that it reveals only those patterns that the researcher needs, and does not consider the properties of the system S, which are not essential for this study.

Thus, characterizing the problem of modelling in general, it is necessary to take into account that from the formulation of the modelling problem to the interpretation of the results obtained, there is a large group of complex scientific and technical problems, the main ones of which include the following: identification of real objects, choice of the type of models, building of models and their machine implementation, the interaction of the researcher with the model in the course of a machine experiment, verification of the correctness of the results obtained in the course of modelling, identification of the main regularities investigated in the process of modelling. Depending on the object of modelling and the type of model used, these problems may have different significance [154].

The process of making a management decision is the transformation of initial information (state information) into output information (control information). The solution can be formal and creative. It is generally accepted that if the transformation of information is carried out using mathematical models, then the solution is considered formal, if the solution appears as a result of the hidden work of the intellect of the person making the decision, then it is creative.

The situations in which the choice of solutions occurs are characterized by:

1. Presence of the goal(s): The need to make a decision is dictated only by the presence of some goal to be achieved. If there is no goal, then there is no need to make any decision.

2. Availability of alternative lines of behavior: Decisions are made in conditions when there is more than one way to achieve the goal. Each of the methods can be characterized by different degrees and different probabilities of achieving the goal, requiring different costs.

3. Presence of limiting factors: Naturally, the decision-maker does not have infinite possibilities. All sets of limiting factors can be divided into three groups: economic factors – money, labor and production resources, time, etc.; technical factors – operating modes, power consumption, reliability, accuracy, etc.; social factors that take into account the requirements of human ethics and morality.

This division is rather arbitrary, since there is no purely formal or purely creative solution. If a solution is developed using a mathematical model, then the knowledge and experience of a person (elements of creativity) are used when creating it, and intuition (also a moment of creativity) – at the moment when it sets one or another value of the parameter of the initial information or chooses from a variety of alternative options, obtained using a mathematical model, one as a solution to control. If the main tool for making a decision is human intellect, then formal methods, the carrier of which is practically all science, are hidden in its knowledge and experience.

In accordance with the division into creative and formal, the whole set of problems accompanying any decision-making process is conditionally divided into two classes: problems of a conceptual nature and problems of a formal mathematical and computational nature.

Conceptual problems include complex logical problems that cannot be solved using only formal mathematical methods and computers. Often these problems are unique in the sense that they are solved for the first time and have not been prototyped in the past. Conceptual problems are usually solved at the level of managers with the involvement of a group of experts, which are highly qualified specialists from various fields of science and practice.

When solving conceptual problems, the greatest weight is given not to formal mathematical methods, but to the erudition, experience and intuition of people. Formal methods here play an auxiliary role as a means that facilitates and organizes the heuristic activity of people. Conceptual problems include, in particular, such problems as the analysis and selection of goals, the identification of sets of indicators characterizing the consequences of the decision made, the choice of optimality criteria from among them, etc. The formalization of heuristic procedures is the content of the so-called informal decision-making theory.

The decision making process is a complex iterative procedure. The block diagram of the decision-making process can be as shown in **Fig. 4.1**.

General formulation of the decision-making problem. Let the efficiency of the choice of a particular solution be determined by some criterion F, which allows quantitative representation. In the general case, all the factors on which the effectiveness of the choice depends can be divided into two groups:

a) controlled (managed) factors, the choice of which is determined by decision-makers. Let's designate these factors as $X_1, X_2, \ldots, X_L$;

b) uncontrollable (uncontrollable) factors characterizing the conditions in which the choice is made and which the decision maker cannot influence. The composition of uncontrollable factors may include the time t. Uncontrollable factors, depending on their awareness of them, are divided into three subgroups: *deterministic* uncontrollable factors – non-random fixed values, the values of which are fully known, $A_1, A_2, \ldots, A_P$); *stochastic* uncontrollable factors – random variables and processes with known distribution laws, $Y_1, Y_2, \ldots, Y_g$; *uncertain* uncontrollable factors, for each of which only the area within which the distribution law is located is known, the values of uncertain factors are unknown at the time of decision making, $Z_1, Z_2, \ldots, Z_Z$.

In accordance with the selected factors, the optimality criterion can be represented as:

$$F=F(X_1, X_2, \ldots, X_L, A_1, A_2, \ldots, A_P, Y_1, Y_2, \ldots, Y_g, Z_1, Z_2, \ldots, Z_Z, t).$$

The values of the controlled factors are usually limited by a number of natural reasons, for example, the limited availability of resources. That is, the regions $\Omega x_1, \Omega x_2, \ldots, \Omega x_L$ of the space are defined (are), inside which the possible (admissible) values of the factors $X_1, X_2, \ldots, X_L$ are located. Similarly, the range of possible values of uncontrollable factors can be limited. The values X, A, Y, Z in the general case can be scalars, vectors, matrices.

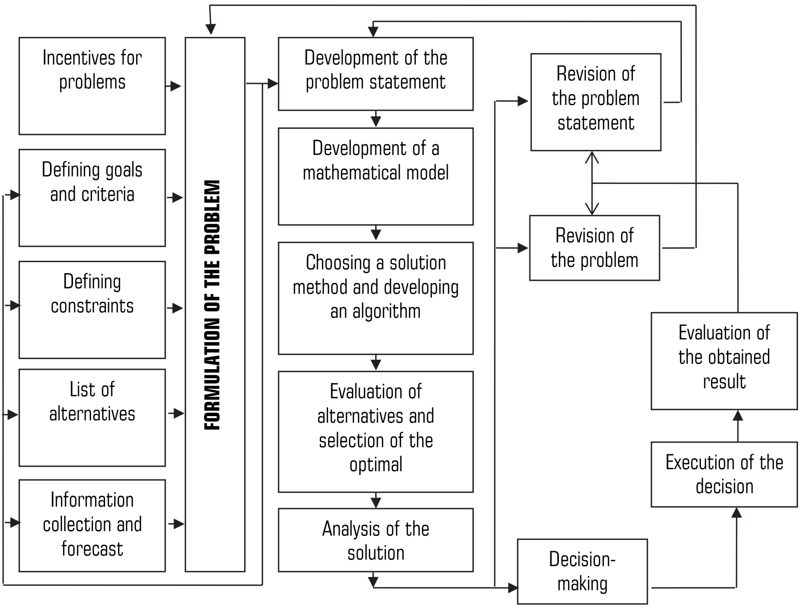


Fig. 4.1 Block diagram of the decision making process

Since the optimality criterion is a quantitative measure of the degree of achievement of the control goal, mathematically, the control goal is expressed in the desire to maximize (or decrease) the value of the criterion F, which can be written as: $F \rightarrow \max$ (или min).

The means for achieving this goal is the appropriate choice of controls $X_1, X_2, \ldots, X_L$ from the areas $\Omega x_1, \Omega x_2, \ldots, \Omega x_L$ of their admissible values. Thus, the general formulation of the decision-making problem can be formulated as follows: for given values and characteristics of fixed uncontrollable factors $A_1, A_2, \ldots, A_P, Y_1, Y_2, \ldots, Y_g$, taking into account the uncertain factors $Z_1, Z_2, \ldots, Z_Z$, find optimal values $X_{1\text{opt}}, X_{2\text{opt}}, \ldots, X_{L\text{opt}}$ from the regions $\Omega x_1, \Omega x_2, \ldots, \Omega x_L$ of their admissible values, which, if possible, would turn the optimality criterion F.

Since production tasks, first of all, are characterized by multi-criteria, let's consider the problems of decision-making in these conditions.

Let's suppose, as before, it is necessary to choose one of the set of solutions X from the region Ω_X of their admissible values. But, unlike the one considered earlier, each selected solution is evaluated by a set of criteria $f_1, f_2, \ldots, f_k$, which may differ in their coefficients of relative importance $(\gamma_1, \ldots, \gamma_k)$. The criteria $f_q(x)$, $q = \overline{1,k}$ are called particular or local criteria, they form an integral or vector criterion of optimality $F = \{f_q\}$. The coefficients γ_q, $q = \overline{1,k}$ form the vector of importance $\Gamma = (\gamma_q)$. Each local criterion characterizes some local goal of the decision being made. The optimal solution X must satisfy the relation:

$$F = F(X) = \underset{X \in \Omega_x}{\text{opt}} \left[F(X), \Gamma \right],$$

where F – optimal solution to the integral criterion; opt – optimization operator, it defines the chosen optimization principle.

The area of admissible solutions Ω_X can be divided into two non-intersecting parts: Ω_X^a – area of agreement, in which the quality of the solution can be improved simultaneously according to all local criteria or without reducing the level of any of the criteria; Ω_X^C – the area of compromises, in which an improvement in the quality of a solution according to some local criteria leads to a deterioration in the quality of a solution according to others. It is obvious that the optimal solution can only belong to the area of compromises, since in the area of agreement the solution can and should be improved according to the corresponding criteria. Highlighting the area of compromise narrows the area of possible solutions, but to choose a single solution, it is necessary to choose a compromise scheme, that is, to reveal the meaning of the optimization operator opt. This choice is subjective.

Let's consider the main compromise schemes, assuming first that all local criteria are normalized (that is, have the same dimension or are dimensionless) and are equally important. It is convenient to consider the analysis by passing from the space Ω_X of selected solutions X to the space Ω_k of possible (admissible) local criteria $F = \{f_1, f_2, \ldots, f_k\}$, dividing it into the region of agreement and the region of compromises. Then the previously formulated optimization model can be rewritten as:

$$F = F(X) = \underset{X \in \Omega_x}{\text{opt}}\, k\left[F(X), \Gamma \right] = \underset{F \in \Omega_f}{\text{opt}}\, k\left[F, \Gamma \right].$$

The main compromise schemes are: the principle of uniformity; the principle of just concession; the principle of highlighting one optimized criterion; the principle of successive assignment, etc. some of which are modified and used above in the previous sections.

The uniformity principle proclaims the expediency of choosing a solution that would achieve a certain «uniformity» of indicators for all local criteria. The following implementations of the principle of uniformity are used.

The equality principle is formally expressed as follows:

$$F = \underset{F \in \Omega f}{\text{opt}}\, k F = \left(f_1 = f_2 = \ldots = f_k\right),$$

that is, the optimal option is the one that belongs to the area of compromise, in which all the values of the local criteria are equal to each other. However, the case $f_1 = f_2 = \ldots = f_k$ may not fall into the area of compromises or not at all belong to the area of admissible options.

The maximin principle is formally expressed as follows:

$$F = \underset{F \in \Omega f}{\text{opt}}\, k = \max_{F \in \Omega_f} \min_{1 \le q \le k}.$$

If this principle is applied, the option with the minimum values of the local criteria is selected from the area of compromises, and among them the option with the maximum value is sought. Uniformity in this case is ensured by «pulling up» the criterion with the lowest level.

The quasi-equality principle is that they strive to achieve approximate equality of all local criteria. The approximation is characterized by a certain value β. This principle can be used in a discrete case.

It should be noted that the principles of equality, despite their attractiveness, cannot be recommended in all cases. Sometimes even a small deviation from uniformity can give a significant increase in one of the criteria.

The fair assignment principle is based on comparing and assessing the increase and decrease in the value of local criteria. The transition from one option to another, if both of them belong to the area of compromises, is inevitably associated with improvement in some criteria and deterioration in others. Comparison and assessment of changes in the value of local criteria can be made according to the absolute value of the increase and decrease in criteria (the principle of absolute assignment), or according to the relative (the principle of relative assignment).

The absolute assignment principle can be formally expressed using the following notation:

$$F = \underset{F \in \Omega f}{\text{opt}}\, kf = \left\{ F \,/ \sum_{j \in J^+} \Delta f_j \ge \sum_{i \in I^-} \Delta f_i \right\},$$

where J^+ – subset of dominated criteria, that is, those for which $\Delta f_j > 0$; I^- – a subset of minorized criteria, that is, those for which $\Delta f_j < 0$; Δf_j, Δf_j – absolute value of the criteria increment; / – the symbol «the one for which».

Thus, it is considered advisable to choose an option for which the absolute value of the sum of the reduction of one or more criteria does not exceed the absolute value of the sum of the increase in the remaining criteria. It can be shown that the principle of maximizing the sum of criteria corresponds to the principle of absolute assignment:

$$F = \underset{F \in \Omega f}{\mathrm{opt}}\, kf = \max_{F \in \Omega_f} k \sum_{q=1}^{k} f_q .$$

The disadvantage of the principle of absolute concession is that it allows for a sharp differentiation of the levels of individual criteria, since a high value of the integral criterion can be obtained due to the high level of some local criteria with relatively small values of other criteria.

The relative assignment principle can be written as:

$$F = \underset{F \in \Omega f}{\mathrm{opt}}\, kF = \left\{ F \,/ \sum_{j \in J^+} X_j \geq \sum_{i \in I^-} \Delta X_i \right\},$$

where $X_j = \Delta f_j / f_j^{\max}$: $X_i = \Delta f_i / f_i^{\max}$ – relative changes in criteria; $f_j^{\max}$, $f_i^{\max}$ – maximum values of the criteria.

It is advisable to choose the option in which the total relative level of decrease in some criteria is less than the total relative level of increase in other criteria.

It is possible to say that the principle of relative assignment corresponds to the model of maximizing the product of criteria:

$$F = \underset{F \in \Omega f}{\mathrm{opt}}\, kf = \max_{F \in \Omega_f} k \sum_{q=1}^{k} f_q .$$

The principle of relative concession is very sensitive to the value of the criteria, and due to the relativity of the concession, the «price» of the concession is automatically reduced for local criteria with a large value and vice versa. As a result, the levels of local criteria are significantly smoothed. An important advantage of the principle of relative assignment is also the fact that it is invariant to the scale of changes in the criteria, that is, its use does not require preliminary normalization of local criteria.

The principle of highlighting one optimized criterion can formally be written as follows:

$$F = \underset{F \in \Omega f}{\mathrm{opt}}\, kf = \max_{F \in \Omega_f} kf_i ,$$

where f_i – criterion to be optimized under the conditions: f_i – admissible value of the criterion.

One of the criteria is optimizable, and the option is chosen that achieves the maximum of this criterion. Restrictions are imposed on other criteria.

Consistent assignment principle. Let's suppose that the local criteria are arranged in decreasing order of importance: first the main criterion f_1, then the other auxiliary criteria f_2, f_3, … As before, let's believe that each of them should be maximized. The procedure for building a compromise solution is as follows. First, a solution is found that maximizes the main criterion f_1. Then, based on practical considerations, for example, from the accuracy with which the initial data are known, a certain «concession» f_1 is assigned, which is admissible in order to maximize the second criterion f_2. Let's impose on the criterion f_2 the requirement that it be less than $f_1^{\max}-\Delta f_1$, where $f_1^{\max}$ – maximum possible value f_1, and with this restriction we are looking for a variant that makes f_2 maximum. Further, a «concession» is again assigned in the criterion f_2, at the cost of which one can maximize f_3, and so on.

This method of building a compromise solution is good because it clearly shows at the cost of what kind of «concession» in one criterion a gain in another is obtained. The freedom to choose a solution, acquired at the cost of even insignificant «concessions», may turn out to be significant, since in the region of the maximum, the effectiveness of the solution usually changes very little.

Earlier it was assumed that the best value is considered to be the greater value of local criteria, that is, the problem of maximizing the integral criterion was solved.

If the lower value of the criteria is considered the best, then from the problem of maximization one should go to the problem of minimization. If a number of criteria need to be maximized, and the rest to be minimized, then the following relation can be used to express the integral criterion:

$$\text{opt } kf = \max_{F\in\Omega_f}\left[\left(\prod_{q=1}^{l} f_q\right)\left(\prod_{q=l+1}^{k} f_q\right)^{-1}\right]$$

or

$$\text{opt } kF = \max_{F\in\Omega_f}\left[\prod_{q=1}^{l} f_q + \left(\prod_{q=l+1}^{k} f_q\right)^{-1}\right],$$

where f_q, $q=\overline{1,l}$ – local criteria that necessary to maximize; f_q, $q=\overline{(l+1),k}$ – local criteria that necessary to minimize.

In some cases, the minimized criteria can be replaced by their inverse ones, and then only the maximization problem is solved. An important stage in solving the problem under consideration is the stage of criteria normalization, as well as assignment and consideration of their priorities.

The problem of criteria normalization arises in all vector optimization problems in which the local optimality criteria have different units of measurement. The exception is those tasks in which the principle of relative concession is applied as a compromise scheme.

The criteria normalization is based on the concept of an «ideal vector», that is, a vector with «ideal» parameter values $F^*=(f_1^*, f_2^*, \ldots, f_k^*)$.

In the normalized space of criteria, instead of the actual value of the criterion f_q, a dimensionless quantity is considered: $f_q^*=f_q/f_q^*$, $q=\overline{1,k}$.

If a large criterion value is considered the best and if $f_q^k\neq 0$, then $f_q^*=[0, 1]$. A successful solution to the problem of normalization largely depends on how correctly and objectively it is possible to determine the ideal values f_q^*. The way of choosing the ideal vector f^i determines the way of normalization. Let's consider the main methods of normalization.

The ideal vector is determined by the given values of the criteria: $F^i = F^g = \{g^g\}$, $q = \overline{1,k}$. The disadvantage of this method is the complexity and subjectivity of the assignment F^g, which leads to the subjectivity of the optimal solution.

As an ideal vector, a vector is selected whose parameters are the maximum possible values of local criteria: $F^i = F_{\max} = \{f^1_{\max}, f^2_{\max}, \ldots, f^k_{\max}\}$. The disadvantage of this method is that it essentially depends on the maximum possible level of local criteria. As a result, the equality of criteria is violated and preference is automatically given to the option with the highest value of the local criterion.

The maximum possible spread of the corresponding local criteria is taken as the parameters of the ideal vector, that is, $f_q^i = f_q^{\max} - f_q^{\min}$, $q = \overline{1,k}$.

Other methods of normalization are also known. Criteria normalization is essentially a transformation of the criteria space, in which the problem of choosing a variant becomes more clear.

Methods for setting and taking into account the priority of criteria. The priority of local criteria can be set using a number of priority, priority vector, weight vector.

The priority series $\overline{R}$ is an ordered set of indices of local criteria $\overline{R} = \{1, 2, \ldots, k\}$, the criteria, the indices of which are on the left, dominate the criteria, the indices of which are on the right. In this case, dominance is qualitative: the f_1 criterion is always more important than f_2, etc. In this case, if among the criteria there are equal priority, they are highlighted in a number of priority by parentheses, for example: $\overline{R} = \{1, 2, (3, 4), \ldots, k\}$.

The priority of the criteria can be specified by a priority vector: $\Gamma = \{\gamma_1, \gamma_2, \ldots, \gamma_k\}$ the components of which are relations that determine the degree of relative superiority in importance of two neighboring criteria from a number of priorities, namely: the value λ_q determines how much the criterion f_q is more important than the criterion f_{q+1}. If some criteria f_q and f_{q+1} are equivalent, then the corresponding component $\gamma_q = 1$. For the convenience of calculations, let's usually set $\gamma_k = 1$. The priority vector Γ is determined as a result of pairwise comparison of local criteria, pre-ordered in accordance with the priority series $\overline{R}$. Obviously, any component of the priority vector satisfies the relation: $\gamma_q \geq 1$, $q = 1, \ldots, k$.

The weight vector: $\beta = \{\beta_1, \beta_2, \ldots, \beta_k\}$ is a k-dimensional vector, the components of which are related by the relations:

$$0 \leq \beta_q \leq 1,\ q = \overline{1,k},\ \sum_{q=1}^{k} \beta_q = 1.$$

The component β_q of the vector β has the meaning of a weight coefficient that determines the relative superiority of the f_q criterion over all the others. The components of the vectors Γ, β are related by the relations $\gamma_q = \beta_q / \beta_{q+1}$.

The priority of the criteria is easier to set using the priority vector, since its components are determined by comparing the importance of only two adjacent criteria, and not the entire set of criteria, as when setting the weight vector. Moreover, it is convenient to do this sequentially, starting with the last pair of criteria, putting $\gamma_k = 1$. It can be shown that for $\gamma_k = 1$:

$$\beta_q = \prod_{q=1}^{l} \gamma_i \left(\sum_{q=1}^{k} \prod_{i=q}^{k} \gamma_i \right)^{-1}.$$

If the priority of the criteria is set in the form of a series, then the principle of «hard priority» is applied when choosing the optimal option, in which sequential optimization is carried out. At the same time, an increase in the level of criteria with low priorities is not allowed if there is even a slight decrease in the value of a criterion with a higher priority.

If a priority vector Γ or a weight vector β are specified, then the principle of «flexible priority» can be used when choosing the optimal option. In this case, the variant is evaluated according to a weighted vector criterion, where the components of the vector $\{\beta_1 f_1, \beta_2 f_2, \ldots, \beta_k f_k\}$ are used as the components of the criteria vector $\{f_1, f_2, \ldots, f_k\}$. In this case, all the considered principles of choosing an option in the area of compromises (the principle of equality, fair concession, etc.) can be applied with the replacement of f_q by $\beta_q f_q$.

An example of a multicriteria decision-making problem is the previously considered problem of choosing the optimal operating mode of the reforming unit in the following interpretation. The optimal operating mode of the facility is characterized by the following local criteria: the volume of the output product – catalyzate – f_1, the octane number of the product – f_2, catalyst stability – f_3, etc. Let these local criteria in this situation have the following relative importance for the decision maker: γ_1, γ_2, γ_3, etc. respectively. Then, when using the method of absolute concession for the case of three local criteria, the best mode of operation will be such for which:

$$F = \max_i \left[\sum_{q=1}^{3} \beta_q f_q \right],$$

where i – i-th operating mode of the reforming unit $i = 1, \ldots, n$.

$$\beta_1 = \frac{\gamma_1 \gamma_2 \gamma_3}{\gamma_1 \gamma_2 \gamma_3 + \gamma_2 \gamma_3 + \gamma_3};$$

$$\beta_2 = \frac{\gamma_2 \gamma_3}{\gamma_1 \gamma_2 \gamma_3 + \gamma_2 \gamma_3 + \gamma_3};$$

$$\beta_3 = \frac{\gamma_3}{\gamma_1 \gamma_2 \gamma_3 + \gamma_2 \gamma_3 + \gamma_3}; \ \gamma_3 = 1.$$

Thus, decision making is a science and an art. The role of this decision is enormous. The most important question for the successful functioning of an organization is how the organization can identify its problems and solve them. Each solution is aimed at some problem, and the right solution is the one that best meets the goals of the organization.

4.2 CREATION OF THE STRUCTURE AND BASIC BLOCKS OF A COMPUTER DECISION-MAKING SYSTEM BASED ON OBJECT MODELS

In production, a decision-maker (facility manager, technologist, economist, ecologist) often finds itself in a situation where, in order to make an optimal decision, it is necessary to process large amounts of information, consider many alternatives, take into account the influence of various factors, assess the consequences of a particular decision under conditions of uncertainty. This situation arises when it is necessary to cope with production tasks when managing multi-criteria objects, such as technological objects of oil refining.

To solve such problems, computer systems for modelling and decision making (CSM-DM) are very useful. Such systems combine the methods of modelling, decision-making and the capabilities of modern computer technology, which can significantly improve and speed up the optimization procedure. The CSM-DM includes the following main blocks: a set of algorithms for solving DM problems, a system of models, a knowledge and data base, a model identifier and a user interface. These blocks are connected by information streams, each of them performs certain functions [155, 156].

The main feature of most production facilities of oil refining and petrochemicals is the lack of clarity of the initial information. In these cases, as already noted, it is necessary to formalize the knowledge and judgments of decision makers, specialist experts, which are of a qualitative nature. To solve such fuzzy problems of optimization and decision-making, it is necessary to include elements of intellectualization in the CSM-DM, allowing to communicate with it in natural or professional languages. These capabilities are achieved on the basis of artificial intelligence methods [157], including a knowledge base, a block of logical inference and explanation of results, algorithms for multi-criteria fuzzy optimization (solving multi-criteria problems of fuzzy mathematical programming) and an intelligent interface [158].

CSM-DM creation for the selection of optimal operating modes of a production facility can be carried out in the following main stages:

1. Identification of the problem area and tasks to be solved, meaningful formulation of DM problems.
2. Formalization of knowledge of decision makers and expert experts about the object and task.
3. Creation of a knowledge and data base.
4. Development of a complex of object models.
5. Algorithmization of optimization problems and decision making.
6. Development of an intellectualized user interface.
7. Software implementation of the developed models and algorithms.

The structure of a computer system for modelling and making the optimal decision on the management of technological objects of oil refining, as well as for other industries, can be represented in the form of **Fig. 4.2** [154].

Let's consider the functional purpose of the main CSM-DM blocks.

The user – the decision maker (in our cases – the operator-technologists) selects the operation mode of the facility that provides the optimal values of the local criteria, as a rule, economic, technological and environmental. The choice of a solution is carried out depending on the current situation in production, for example, on the plan for the release of products, the composition of feedstock, requirements for product quality, environmental safety, etc., taking into account the importance of local criteria and imposed restrictions (on the values of control and operating parameters, local criteria).

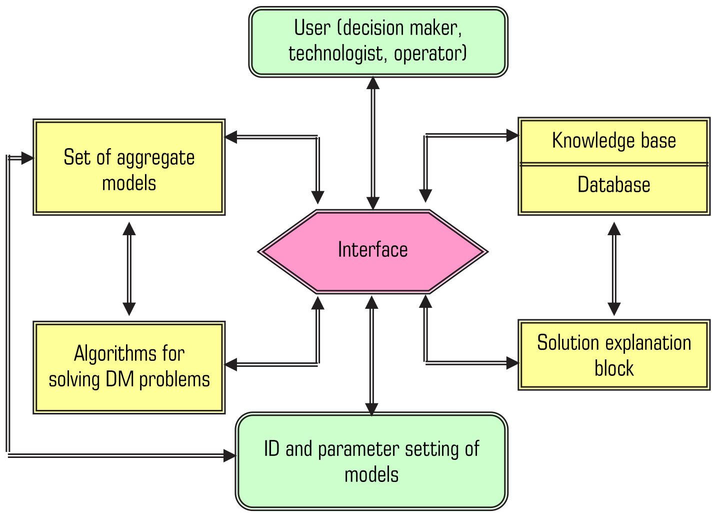


Fig. 4.2 CSM-DM structure

To solve this problem, the decision maker uses a package of object models, algorithms for solving multicriteria problems of mathematical programming (optimization problems) and, if necessary, a knowledge and data base, a block for explaining the solution, etc. When setting up and adapting the system to new operating conditions, decision makers, experts can act as an expert for filling the knowledge base, collecting and processing qualitative indicators [159].

The block of a complex of models contains various models, including fuzzy ones, of individual elements of the production system, combined into a single package that allows systemic modelling of the operation of the object as a whole. These models are designed to determine (calculate) the values of local criteria depending on the values of the input actions.

A set of algorithms for solving DM problems, for example, the algorithms proposed in this work – MC+MM, PO+IP, A(R)C+PO, their combinations, etc. is intended for solving multi-criteria decision-making problems, incl. and in a fuzzy environment. These algorithms, based on a complex of models, a knowledge base and a block for explaining the solution, search for rational modes of operation of the object according to the selected criteria and determine the recommended values of control actions that provide these modes. The choice of the final decision, as a rule, remains with the decision maker.

The knowledge base and database are designed to store formalized knowledge of expert specialists, subject matter researchers and statistical data on production. Information from these blocks is used in the process of analyzing the main indicators of the object and making decisions, for drawing up production reports and adapting models to new conditions.

The interface is designed to provide a convenient dialog mode for the user to work with the system when controlling an object, as well as when implementing a number of other CSM-DM functions. In the course of working with the system, if necessary, the following is implemented: displaying the scheme of production facilities and information about the ecological state of these facilities, displaying the values of control parameters and the results obtained on the screen in a form convenient for the user, visual observation of the process of optimizing the operating modes of the facility, entering and adjusting the necessary parameters to optimize and ensure the environmental safety of production.

The block of explanation of the decision implements the strategy of prompting and explaining the results obtained. Explanations of the results obtained in a concise and convenient form for human analysis are carried out by recording all the considerations adopted by the system during alternative elections.

To adjust the adaptation of models of technological objects to new operating conditions, an identifier of the model parameters is added to the computer optimization systems. This block is a program that checks the adequacy of the models and, if necessary, recalculates (identifies) the parameters of the models.

The effectiveness of such intelligent CSM-DM for managing various production is determined by the quality of formalization and presentation of knowledge, the developed models and algorithms for solving control problems, as well as the convenience of the user interface.

The problems of modelling and optimization of production, in many cases, are formalized and solved under conditions of uncertainty. To solve such problems, information from a person is mainly used. In this regard, the efficiency of solving the considered problems largely depends on methods for building fuzzy models and algorithms for solving optimization problems in a fuzzy environment. The method of system modelling and algorithms for multicriteria optimization, taking into account the fuzziness of information, proposed in the monograph, can be effectively implemented with the intensification of various production facilities based on mathematical methods.

The results of pilot industrial tests of the research results confirmed the correctness of the theoretical results described in Sections 2 and 3. For example, the expected economic effect from the use of the created models and algorithms for optimizing the operating modes of the catalytic reforming unit is more than 1.8 million tenge, which is achieved by increasing the yield of target products with the required quality and prompt solution of planning and management tasks, depending on the current situation in production.

The advantages of the proposed CSM-DM over similar computer systems are that it includes a set of algorithms for modelling interconnected technological units and a multicriteria selection of optimal operating modes of an object that are efficient in a fuzzy environment, an intelligent interface.

4.3 SOFTWARE IMPLEMENTATION OF THE DEVELOPED MODELS AND DESCRIPTION OF THE INTERFACE OF THE SYSTEM FOR MODELLING THE UNITS OF THE REFORMING UNIT

Based on the results of the analysis and comparison of the selection criteria for the software implementation of the developed models of the reforming process, the Visual Basic environment was chosen in this work. The main criterion when choosing a programming tool was convenience and prostate. The text of the main blocks of the compiled program and modules are given below.

Main modules of the program

```
Attribute VB_Name=«Module1»

Function Y1(X11, X21, X31, X41, X51) As Double
Y1=(0.395 * X11 + 12.153846154 * X21 + (–0.032113821) * X31 – 0.948 * X41 _
+ 0.01975 * X51 + 0.0049375 * X11 ^ 2 + 9.349112426 * X21 ^ 2 +
(–0.000065272) * X31 ^ 2 _
+ (–0.03792) * X41 ^ 2 + 0.000049375 * X51 ^ 2 + 0.227884615 * X11 * X2 +
0.000100356 * X11 * X31 _
+ 0.001975 * X11 * X41 + 0.00049375 * X11 * X51 + 0.037054409 * X21 * X31 +
(–0.486153846) * X21 * X41 _
+ (–0.000642276) * X31 * X41)
End Function

Function Y1a(X1a, X2a, X3a, X4a, X5a) As Double
Y1a=((0.398481013) * X1a + (12.107692308) * X2a + (–0.031862348) * X3a +
(–0.98375) * X4a _
+ (0.019675) * X5a + (0.005044063) * X1a ^ 2 + (9.313609467) * X2a ^ 2 +
(–0.000064499) * X3a ^ 2 _
+ (–0.040989583) * X4a ^ 2 + (0.000049187) * X5a ^ 2 + (0.229892892) * X1a *
X2a + (0.00010083) * X1a * X3a _
```

```
+ 0.002075422 * X1a * X4a + (0.000498101) * X1a * X5a + (0.036764248) * X2a *
X3a + (–0.504487179) * X2a * X4a _
+ (–0.000663799) * X3a * X4a)
End Function

Function Y1b(X1b, X2b, X3b, X4b, X5b) As Double
Y1b=((0.398983482) * X1b + (12.076923077) * X2b + (–0.031589537) * X3b +
(–1.023913043) * X4b _
+ (0.019625) * X5b + (0.005069676) * X1b ^ 2 + (9.289940828) * X2b ^ 2 +
(–0.00006356) * X3b ^ 2 + (–0.044517958) * X4b ^ 2 _
+ (0.000049063) * X5b * 2 + (0.230182778) * X1b * X2b + (0.000100348) * X1b *
X3b + (0.002168388) * X1b * X4b + (0.000498729) * X1b * X5b _
+ (0.036449466) * X2b * X3b + (–0.525083612) * X2b * X4b + (–0.000686729) * X3b * X4b)
End Function

Attribute VB_Name=«Module2»
Function Y2(X12, X22, X32, X42, X52) As Double
Y2Y3=((500#) * X12 + (7142.8571429) * X22 + (10.101010101) * X32 +
(–1458.3333333) * X42 _
+ (25#) * X52 + (6.25) * X12 ^ 2 + (5102.0408163) * X22 ^ 2 + (0.020406081) *
X32 ^ 2 + (–60.763888889) * X42 ^ 2 _
+ 0.0625 * X52 ^ 2 + (178.57142857) * X12 * X22 + (0.252525253) * X12 * X32 +
(–15.625) * X12 * X42 + (1.25) * X12 * X52 _
+ (–297.61904762) * X22 * X42 + (2.525252525) * X32 * X42 + (–0.050505051) *
X32 * X52 + (–1.041666667) * X42 * X52)
End Function

Attribute VB_Name=«Module3»
Function Y3(X143, X243, X343, X443, X543) As Double
Y3=(0.435) * X143 + (–20.076923077) * X243 + (0.052834008) * X343 +
(–0.725) * X443 _
+ (0.042439024) * X543 + (0.0054375) * X143 ^ 2 + (–15.443786982) * X243 ^ 2 +
(0.000106951) * X343 ^ 2 + (–0.030208333) * X443 ^ 2 _
+ (0.00010351) * X543 ^ 2 + (0.000220142) * X143 * X343 + (0.000265244) *
X143 * X543 + (–557692308) * X243 * X443 + (0.000085909) * X343 * X543
End Function

Attribute VB_Name=«Module4»
Function Y4(X154, X254, X354, X454, X554) As Double
```

```
Y4=((0.40625) * X154 + (–9.285714286) * X254 + (0.065922921) * X354 +
(–0.541666667) * X454 _
+ (–0.016049383) * X554 + (0.005078125) * X154 ^ 2 + (–6.632653061) * X254 ^ 2 +
(0.000133718) * X354 ^ 2 + (–0.022569444) * X454 ^ 2 _
+ (–0.000039628) * X55 ^ 2 + (0.000659229) * X154 * X354 + (–0.386904762) *
X254 * X454 + (–0.011463845) * X254 * X554 + (–0.000668724) * X454 * X554)
End Function

Attribute VB_Name=«Module5»
Function Y8(X18, X28, X38, X48, X58) As Double
Y8=((0.022) * X18 + (–0.942857143) * X28 + (0.002677485) * X38 +
(–0.036666667) * X48 _
+ (0.002146341) * X58 + (0.00034375) * X18 ^ 2 + (–0.897959184) * X28 ^ 2 +
(0.000007241) * X38 ^ 2 + (–0.002291667) * X48 ^ 2 _
+ (0.000007852) * X58 ^ 2 + (0.000022312) * X18 * X38 + (0.000013415) * X18 *
X58 + (–0.039285714) * X28 * X48 + (0.000002177) * X38 * X58)
End Function
```

Let's show description of the interface of the computer system being developed. The main menu of the system is shown in **Fig. 4.3**.

As can be seen from the above menu, the proposed computer system for modelling and decision-making consists of three main subsystems: a modelling system; decision-making system and subsystem, which describes the process technology and provides process diagrams.

In this work, a subsystem for modelling the reforming process is fully implemented on the basis of the developed mathematical models of the main units of the catalytic reforming unit of the LG unit of the Atyrau refinery. Let's give a more detailed description of this subsystem.

Fig. 4.3 shows the main menu, where the «Modelling system» menu is open, i.e. when press «Modelling system» submenus open: «System modelling of the reforming process»; «Mathematical models of the main units of the block»; «Linguistic models of the reforming process»; «Setting the coefficients of the models».

Selecting «System modelling of the reforming process» opens a window where the process is simulated directly (**Fig. 4.4**). As can be seen from **Fig. 4.4**, in the simulation mode, for convenience, the Interface on the upper part contains the names of the main operating-input parameters $(x_1, x_2, x_3, x_4, x_5)$, changing which the modelling process is carried out and the search for the optimal operating mode of the reforming unit units. The influence of these parameters on the process was investigated above. The menu shows the intervals for changing each of the input-mode parameters.

To select a modeled reforming reactor (R-2, R-3, R-4, 4a), there is a corresponding window in the interface. To change the value of each of the parameters x_1, x_2, x_3, x_4, x_5, there are corresponding windows on the right side.

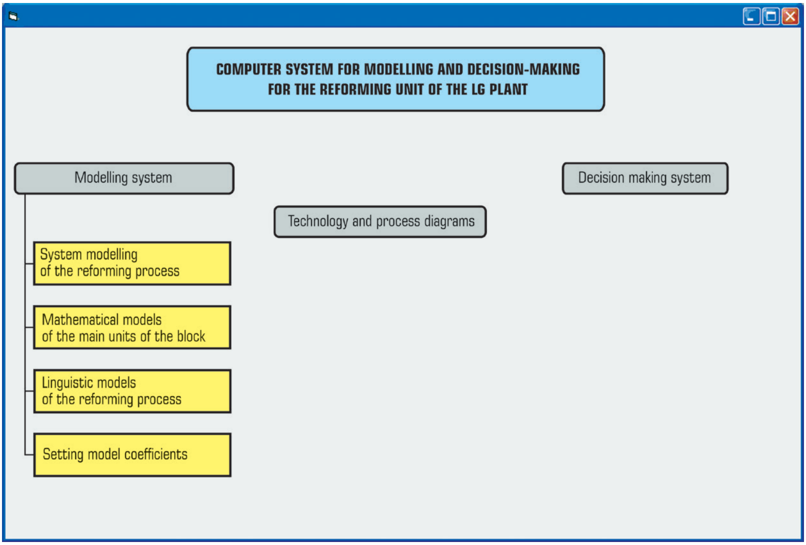


Fig. 4.3 Main menu of the developed system

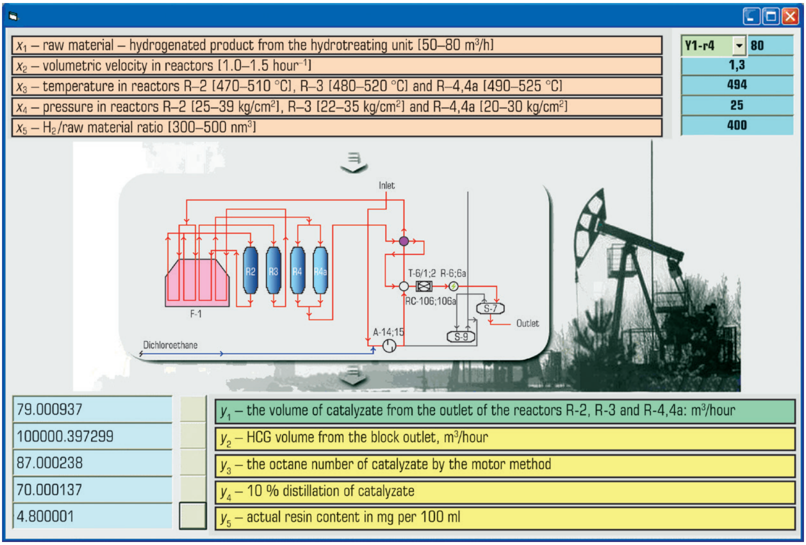


Fig. 4.4 Modelling of the reforming process

The lower part of the window shows the simulation results – the values of the output parameters of the process – y_j, $j = 1,2,\ldots$ (the amount of products produced and the quality indicators of the target products). To display a new value of the output parameters when changing the input, it is necessary to click on the button: standing in front of the corresponding y.

Fig. 4.4 shows the results of the search for the optimal operating mode of the reforming unit («manual» search).

Thus, using this subsystem, changing the values of the input parameters and determining the corresponding values of the output parameters, i.e. By simulating various modes of operation of the main units of the rhythforming unit, it is possible to find the optimal mode of the reforming process, i.e. find such values of the input parameters that provide the extreme (optimal) values of the output parameters.

The described mode requires experience and knowledge of the user, as well as time, i.e. not convenient for production workers. For the convenience of using this system in production conditions, it is possible to create a subsystem «Decision making system» based on the set of dialog algorithms for solving multicriteria DM problems developed in Section 3 of this work for choosing the optimal operating modes of the technological complex, taking into account the fuzziness of the initial information. Currently, a simplified version of the A(R)C+PO algorithm has been implemented in software when solving the DM test problem to optimize the operating modes of the catalytic reforming unit. The results obtained are considered in Section 3 (Subsection 3.4). The software implementation of the remaining algorithms is underway. These algorithms allow the user to solve optimization problems in a convenient mode, i.e. carries out an automated search for such values of the input parameters that provide the optimal values of the output parameters – criteria.

The subsystem «Technology and process diagrams» was created at the request of users and contains information on the process technology (given in Section 2) and various process diagrams, as well as information on the conduct of the process.

4.4 RESEARCH RESULTS AND PROSPECTS FOR THEIR APPLICATION

In this subsection, let's summarize and propose a further direction and prospects for the application of the obtained research results.

Thus, in this research work, new promising methods of modelling and decision-making on the choice of optimal modes of operation of complex production facilities have been created using the example of the reforming unit of the LG unit. On the basis of these results, software and other components of an intelligent computer system for modelling and decision-making are created. Theoretical results are obtained that make it possible to solve the problems of mathematical modelling and decision-making under conditions of uncertainty caused by the indistinctness of the initial information and the multicriteria of the optimization object.

The results obtained have been brought up to specific algorithms. The built models of the main units of the reforming block were implemented in software and an interactive system was obtained for modelling the reforming process in order to optimize it.

On the basis of the proposed algorithm for solving DM problems, the specific problem of adopting the optimal operating mode of the reforming unit is solved. The stated problems are solved completely.

The structure of a computer system for modelling and decision-making to optimize the complex of technological units for oil refining is created and described.

The developed CSM-DM structure in the long term makes it easy to expand the software, including new functions and capabilities of the system. In addition, the proposed architecture, in the presence of appropriate hardware and technical (communication device with the object) and additional software, allows to close the control loop, i.e. the computer will directly control the object. The proposed approaches to the creation of models, algorithms for solving multicriteria optimization problems can be effectively used to solve production problems in various industries (petrochemistry, oil and gas, etc.).

In the coming years, the communication systems between the user and the computer must move to a new qualitative level. Text communication, which requires working at the keyboard, will be replaced in the future by voice communication, when the user will enter the information it needs from the voice and receive messages from the system in the same form. The speech form familiar to a person will further increase the comfort of its communication with CSM-DM and will greatly increase the efficiency of such systems.

4.5 CONCLUSIONS OF SECTION 4

1. As the main problems in modelling and solving DM problems, it is possible to note the uncertainty, which complicates the process of mathematical description, and multi-criteria in choosing the optimal mode of operation of the object. To solve these problems associated with the fuzziness and multicriteria of DM problems in a fuzzy environment, it is advisable to use the methods of the theory of fuzzy sets, which make it possible to formalize and effectively use fuzzy information from decision makers, specialist experts and compromise schemes adapted to work in a fuzzy environment.

2. For the effective solution of DM problems, it is advisable to develop a computer system for modelling and decision-making support, which ensures the correct choice of the optimal operating modes of the technological complex. The advantages of such systems proposed in this work over similar systems are that it includes a set of algorithms for modelling interconnected technological units and a set of algorithms for solving multi-criteria DM problems in a fuzzy environment based on quality information, as well as an intelligent interface. The main research results and the prospects for their application are considered.

3. For the software implementation of the developed models and the creation of a convenient intellectualized user interface of the system for modelling and supporting DM, it is necessary to use modern programming tools, including the Prolog language, which can provide an effective knowledge base and user interface.

4. A promising direction in the creation of intellectualized systems is the change of textual communication, which requires work at the keyboard, with voice communication, providing the user to enter the information it needs from the voice, as well as receive messages from the system in the same form. This is due to the fact that the familiar speech form for a person will further increase the comfort of its communication with CSM-DM and will greatly increase the efficiency of such systems.

CONCLUSIONS

The monograph contains new scientifically substantiated results in the field of mathematical modelling and decision-making in a fuzzy environment, as well as the multicriteria of the problems and objects under study, the use of which provides a solution to an important applied problem of the oil refining industry. The research results, the proposed methods and solutions make it possible to effectively solve the production problems of oil refining in a fuzzy environment.

The main scientific results, practical conclusions and recommendations are as follows:

1. In conditions of uncertainty and indistinctness of the initial information for the building of models of interconnected units of technological units, it is recommended to apply the proposed method for creating a complex of interconnected models. Because this method, based on the use of available information of a different nature (theoretical information, experimental statistical data, expert and fuzzy information), allows to build models of interconnected technological units of various types (deterministic, statistical, fuzzy, combined) and combine them into a single package of models.

2. In practice, in real technological objects, due to the fuzzy parameters, two main situations stand out. Situation 1, when the input, operating parameters (temperature regime, pressure regime, etc.) can be measured, i.e. crisp, and some output parameters assessing the quality of the object's work are not measurable, i.e. fuzzy, which are assessed by a person. Situation 2, when both the input, operating and output parameters are not clearly estimated. Depending on this, using the methods of synthesis of the fuzzy and linguistic model of the model proposed in this work, fuzzy models (in the case of Situation 1) and linguistic (in the case of Situation 2) models can be built. On the basis of the proposed methods for synthesizing models in a fuzzy environment, models of the main units of the reforming unit (reactors R-2, R-3, R-4, 4a, furnace F-1) of the LG unit of the Atyrau refinery have been built, which make it possible to carry out system modelling of the operation of the unit under study.

3. When assessing complex objects in conditions of uncertainty and lack of clarity, experts find it difficult or unable to assess their mutual importance. In this case, it is advisable to organize and conduct an expert assessment using the methods of fuzzy sets, in which experts evaluate the object fuzzy, verbally, and the obtained fuzzy information is further processed on the basis of the mathematical apparatus of fuzzy set theories. The paper proposes an algorithm for expert assessment that allows experts to make an assessment at a qualitative level, to process the results of a survey in a fuzzy environment using the methods of theories of possibilities.

4. In the conditions of indistinctness of the initial information, the DM problem for choosing the optimal modes of technological objects is expedient to formulate and lead to NMT problems, for the solution of which in this monograph by modifying various schemes of compromises and optimality principles a set of heuristic algorithms for their solution is proposed. The effectiveness

of these algorithms lies in the fact that they, based on knowledge, experience, intuition and taking into account the preferences of decision makers, experts and making the most of the collected fuzzy information, allows to get effective solutions to production problems in a fuzzy environment.

5. The choice of a specific algorithm from the developed set of algorithms (MC+MM, PO+IP, A(R)C+PO) when solving various tasks for choosing the operating modes of an object depends on the production situation, on the available information and decision maker, as well as on properties of the selected algorithms. The paper proposes a procedure for choosing the most suitable algorithm from the proposed set, depending on the listed factors. On the basis of the A(R)C+PO algorithm, the DM problem of the optimal operating modes of the reforming unit of the LG unit of the Atyrau refinery was solved. The effectiveness of the proposed method for solving DM problems in a fuzzy environment is shown, which is determined by the adequacy of the solution with experimental data, ease of use and performance under uncertainty.

6. The structure and functional blocks of the computer decision support system for the choice of optimal operating modes of technological objects should be created according to the principle of open systems. This is due to the fact that in the future, depending on possible changes, it becomes necessary to supplement new blocks and functions to the existing systems, which should be created and modified. The advantage of the proposed system over similar systems is determined by the fact that it includes a set of algorithms for modelling interconnected technological units and solving multi-criteria DM problems, which are workable in a fuzzy environment, as well as an intelligent interface.

Assessment of the completeness of solutions to the assigned tasks. The tasks set in the work have been completely solved, a systematic analysis of approaches to modelling and decision-making on the management of chemical-technological oil refining systems (using the example of a catalytic reforming unit) has been carried out, and a concept has been created for building models of such systems based on complex information of a quantitative and qualitative nature.

Theoretical results – algorithms for the synthesis of models and solution of DM problems, are practically implemented in the building of models of the investigated object and in the choice of optimal modes of their operation.

Recommendations for the specific use of the results. The proposed methods and algorithms can be used to optimize technological complexes of oil refining, petrochemical and other industries through mathematical modelling and decision making. For the development of models of technological objects, solution of DM problems for the selection of optimal modes of their operation, it is possible to use the proposed algorithms by organizing and conducting expert procedures. It should be emphasized that the main source of information is the decision maker and expert experts, and the collected information is characterized by fuzziness, which requires the use of methods of theories of fuzzy sets and possibilities.

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SYSTEM CONCEPT FOR MODELLING OF TECHNOLOGICAL SYSTEMS
AND DECISION MAKING IN THEIR MANAGEMENT

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