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SPECIAL ISSUE

Models for Managing the Elimination of Consequences of Critical Situations at Oil Refining and Chemical Enterprises

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Abstract—The article is devoted to the development and application of system-dynamic models for managing the process of liquidation of emergency situations at oil-refining and chemical enterprises. A complex of heterogeneous system-dynamic models has been developed, allowing enterprise management according to a criterion that minimizes the deviation of relevant indicators of safe functioning from the values recommended by the decision-maker. A formulation of the problem of managing the process of liquidation of emergency situations is presented, and a comprehensive methodology is proposed, including the construction of cause-and-effect graphs, regression analysis of functional dependencies, numerical solution of a system of nonlinear differential equations, as well as a procedure for correcting the system-dynamic model. The complex of models makes it possible to take into account key safety indicators, external factors, and nonlinear effects, ensuring high accuracy of forecasting and risk analysis. The obtained results can be used in the development of control systems for the process of liquidation of consequences of emergency situations at oil-refining and chemical enterprises of the country, as well as in training systems for facility-level units of the Ministry of Emergency Situations.

Keywords: oil-refining enterprises, chemical enterprises, system dynamics, control systems, chemically hazardous substances, critical situations, nonlinear differential equations, training systems

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1. INTRODUCTION

At present, in connection with the development of new technologies and the complication of production processes, the issues of increasing the safety of the functioning of oil-refining enterprises are becoming one of the priority tasks. Accidents at such enterprises can lead to serious consequences for human health, the environment, and the economy, which makes the issues of increasing the level of industrial safety of oil refineries highly relevant (see Fig. 1).

Industrial safety at oil-refining enterprises is the most important aspect determining the sustainability of production, the prevention of accidents, and the reduction of the economic and environmental consequences of possible incidents. In recent decades, various researchers have studied methods for assessing and managing risks at such enterprises, applying both traditional statistical methods and modern approaches, including machine learning and intelligent data analysis. The

Fig. 1. State of the Achinsk oil refinery after the fire [1].

analysis of the existing literature makes it possible to identify several main directions of research in the field of the safety of oil-refining enterprises, including quantitative risk assessment, modeling of emergency situations, forecasting of equipment failures, and analysis of historical accident data.

One of the effective methods of risk assessment is Fault Tree Analysis (FTA), which is used to analyze possible scenarios of equipment failures and their consequences. In [2], the application of the Fuzzy Fault Tree Analysis (FFTA) method for assessing the risks of fires and explosions in oil storage tanks is considered. The authors note that traditional methods of quantitative risk analysis assume the availability of accurate data on the probability of failure of various elements of the system; however, in practice, such data may be incomplete or inaccurate due to insufficient statistical information. In this work, a combined methodology is proposed that combines traditional fault tree analysis with fuzzy set theory, which makes it possible to take uncertainties into account when assessing the probability of accidents.

Historical analysis of accidents also plays an important role in the development of methods for preventing incidents. In [3], a detailed analysis of 44 accidents at the oil refinery in Skikda (Algeria) over the period from 2002 to 2013 was carried out. The authors considered various incidents, including fires, explosions, and leaks of toxic substances, and identified the key factors contributing to the occurrence of accidents. On the basis of the data analysis, it was established that a significant part of the accidents was caused by equipment failures resulting from outdated infrastructure and insufficient maintenance.

Another important aspect of ensuring safety at petrochemical enterprises is the analysis of fire and explosion risks. In [4], methods for assessing and modeling risks associated with fires and explosions at petrochemical facilities are considered. The study uses a comprehensive approach, including the HAZID methodology for hazard identification, Dow's Fire & Explosion Index (Dow's F&EI) for quantitative risk assessment, as well as software-based modeling of emergency situations using the Process Hazard Analysis Software Tool (PHAST).

Forecasting equipment failures is another important area of research in the field of industrial safety. In [5], a methodology for predicting pipeline failures based on machine learning methods is proposed. The authors use three models—a multilayer perceptron neural network (MLP), a radial basis function neural network (RBF), and multinomial logistic regression (MNL)—for the analysis of historical data on pipeline damage.

Modern technologies for processing textual information are also finding application in the field of industrial safety. In [6], a system for automated risk analysis of oil refineries based on natural language processing (NLP) and the Bidirectional Encoder Representations from Transformers (BERT) model is proposed.

Equipment reliability management and maintenance planning also play an important role in ensuring industrial safety. In [7], a Risk-Based Inspection and Maintenance (RBI&M) methodology is presented, including six stages: identification of the scope of application, functional analysis, risk assessment, quantitative expression of risk, planning of measures, and implementation of works.

Special attention is paid to the study of the domino effect—the escalation of emergency situations due to a primary incident. In [8], a detailed analysis of methods for assessing the domino effect at industrial facilities over the past 30 years was carried out.

Thus, modern studies in the field of industrial safety demonstrate a wide range of methods for risk assessment and management, from classical probabilistic models to intelligent data analysis. The integrated application of these approaches makes it possible to significantly increase the safety of oil-refining enterprises by reducing the probability of emergency situations and mitigating their consequences.

Many researchers and engineers are engaged in developing innovative solutions to reduce risks and increase the reliability of production processes. The developed systems and methods, including control and diagnostic means, undergo thorough testing and demonstrate high efficiency in practice.

Nevertheless, despite many years of research and the achieved results, the existing models and methods do not always make it possible to take into account the complex system of interrelations between internal and external factors affecting the safety of processes, which may negatively affect their reliability. This circumstance makes the application of the mathematical apparatus of system dynamics expedient for increasing the safety of the functioning of oil-refining enterprises.

System dynamics is a method of computer modeling and analysis of complex systems that makes it possible to study their behavior over time under the influence of various factors. This approach is based on the use of differential equations and feedback loops to describe the interrelations between the elements of the system.

Historically, system dynamics was developed by J. Forrester and his colleagues in the middle of the twentieth century for the analysis of industrial and social systems [9].

At present, it is applied in various fields, including production, emergency management, healthcare, analysis of natural disasters, and many others. In production, it is used for process optimization, increasing the efficiency of equipment operation, and resource management, which makes it possible to minimize costs and predict possible failures.

In the field of emergency management, system dynamics helps to model the development of events, assess the consequences of technogenic disasters, and develop effective response plans, which significantly increases the level of safety. In healthcare, it finds application in diagnostics, treatment planning, and resource management, as well as in combating epidemics, where models predict the spread of infections and assess the effectiveness of preventive measures.

In addition, system dynamics is actively used for the analysis and management of the consequences of natural disasters, such as floods, making it possible to develop strategies for minimizing damage and restoring infrastructure. This approach is indispensable in situations where it is necessary to take into account many interrelated factors and predict the development of complex systems.

As shown in [10], this approach makes it possible to take into account nonlinear interactions, feedback loops, and time delays that are characteristic of industrial systems. The authors carried out an analysis of 63 studies in which system dynamics was applied to assess external factors, organizational impacts, and internal causes of accidents.

In the case of the oil-refining industry, a classical example is the analysis of the Bhopal accident, where system dynamics was used to construct models describing the influence of the human factor, technical failures, and organizational decisions on the safety of the functioning of the Union Carbide chemical enterprise [11]. The work considered cause-and-effect relationships between key variables affecting the safety of functioning, such as equipment failure, operator errors, and insufficient maintenance.

In [12], the main shortcomings of traditional methods are emphasized, including their limitations in modeling nonlinear processes and time delays. The authors analyze the application of system dynamics in the context of risk analysis for the oil-refining industry. They also highlight the need to integrate this methodology into the decision-making process, which makes it possible to better predict emergency situations and increase resilience to critical situations in the process of functioning of an oil-refining enterprise. This study presents a model of the actions of the population in the event of an accident at a chemically hazardous facility, taking into account the level of awareness of the enterprise personnel.

In [13], a system-dynamic model used in the system for managing the process of informing the population under emergency situations at oil-refining enterprises is presented. The authors developed a stock-and-flow model that analyses the influence of the frequency of message distribution and the quality of information on people's behavior during chemical accidents.

This article is devoted to the development of new system-dynamic models intended for use in managing the process of liquidation of emergency situations at oil-refining enterprises. These models make it possible to comprehensively assess possible risk factors that may lead to disruption of the normal course of technological processes, to take timely necessary measures to prevent emergency situations, and to reduce the damage from their occurrence.

2. STATEMENT OF THE PROBLEM

Develop mathematical models and methods for managing the process of liquidation of emergency situations at an oil-refining enterprise according to an efficiency criterion that makes it possible, over the time interval $t \in [t_0; t_N]$, to determine control actions in the form of an action plan $p(t) \in P$ and to minimize, under admissible values of environmental disturbances $R(t) \in R$, the objective function

$$Z(p(t)) = \int\limits_{t_0}^{t_N} \sum_{i=1}^{n} \left(K_i^* - K_i(t, R(t), p(t))\right)^2 \gamma_i \, dt \to \min \tag{1}$$

subject to the constraints:

$$\frac{dK_i(t, R(t), p(t))}{dt} = f_i\left(t, K_1(t), \ldots, K_n(t), R(t), p(t)\right), \quad i = \overline{1, n}, \tag{2}$$

$$K_i(t_0) = K_{i0}, \quad i = \overline{1, n},$$

$$t > 0, \quad K_i > 0, \quad i = \overline{1, n},$$

$$K_i^{\min} \leqslant K_i(t, p(t)) \leqslant K_i^{\max}, \quad i = \overline{1, n} \tag{3}$$

and boundary conditions:

$$F_i^{t_0}(K, K', p) = 0, \quad F_j^{t_N}(K, K', p) = 0, \quad i = \overline{1, k_1}, \quad j = \overline{1, k_2}.$$

Here, $K_i(t, p(t))$, $i = \overline{1, n}$, and K_i^* are the relevant indicators of the efficiency of liquidation of a critical situation and their values recommended by the decision-maker, respectively; γ_i is the weight coefficient of the ith indicator; $K_i^{\min}$ and $K_i^{\max}$ are the minimum and maximum values of the efficiency indicator of liquidation of the emergency situation.

Develop mathematical models and algorithms for forecasting, over the time interval $[t_0; t_N]$, changes in the relevant indicators of the efficiency of liquidation of the emergency situation $K_i(t, p(t))$, $i = \overline{1, n}$, for the purpose of determining such time instants $t_j \in [t_0; t_N]$, $j = \overline{1, m}$, when they go beyond the values K_i^* recommended by the decision-maker.

3. MATHEMATICAL MODEL

To solve problems (1)–(3), it is expedient to use the system-dynamic approach and the method of system dynamics [5, 9, 12, 13, 16–19]. Within the framework of this approach, a complex of interconnected mathematical models has been developed, the construction of which involves the implementation of the following stages:

1. Selection of the input variables of the model affecting the safety of the functioning of oil-refining and chemical enterprises in accordance with [14, 15].

2. Development of a cause-and-effect graph between the system variables and external influences.

3. Construction of a system of system-dynamics equations in the general form, the solution of which will make it possible to forecast the values of the variables related to the safety of the functioning of an oil-refining enterprise over various time intervals.

4. Determination of functional dependencies between the model variables using the apparatus of regression analysis.

5. Solution of the system of nonlinear differential equations by a numerical method.

6. If necessary, correction of the mathematical model in order to achieve the required accuracy of calculations.

Selection of Input Variables. The assessment of the safety of the functioning of oil-refining and chemical enterprises is determined in accordance with the requirements of the Federal Law "On the Protection of Population and Territories from Natural and Man-Made Emergencies" [14] and GOST R 22.1.10–2002 "Safety in Emergencies. Monitoring of Chemically Hazardous Objects" [15] (see Fig. 2).

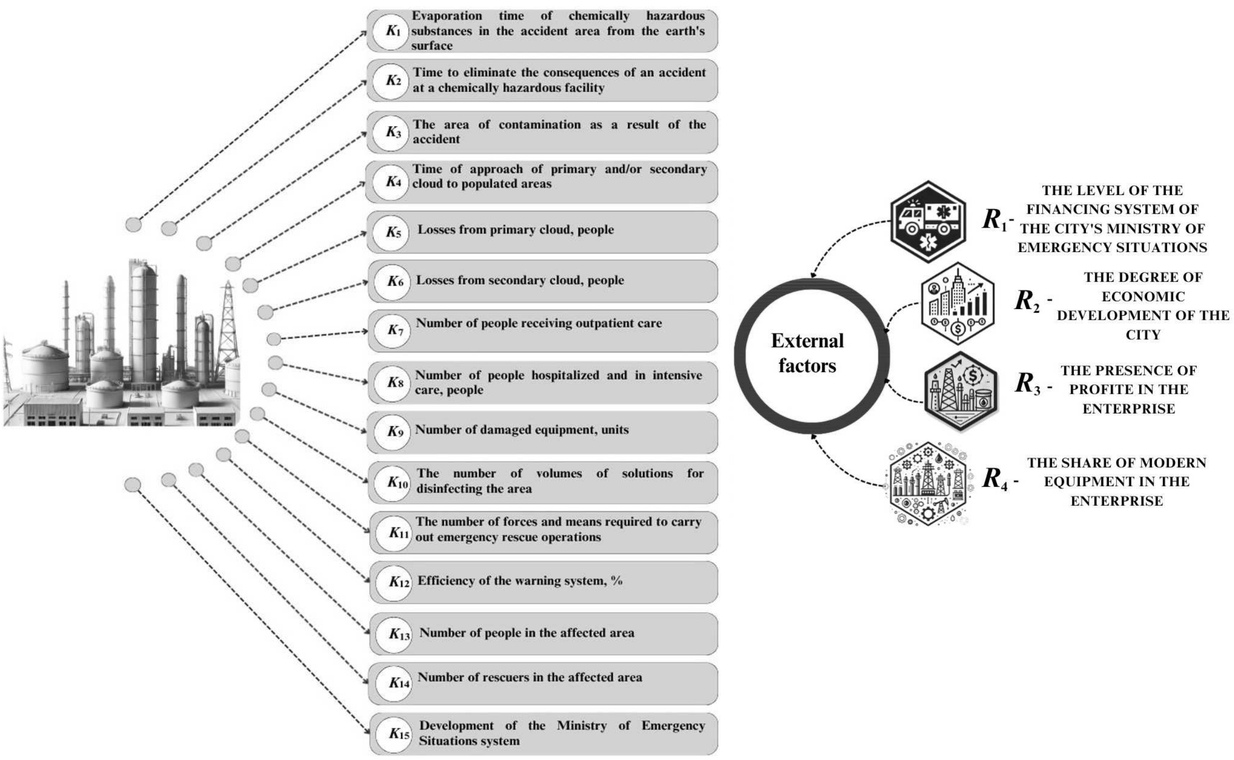

Fig. 2. Input variables of the model.

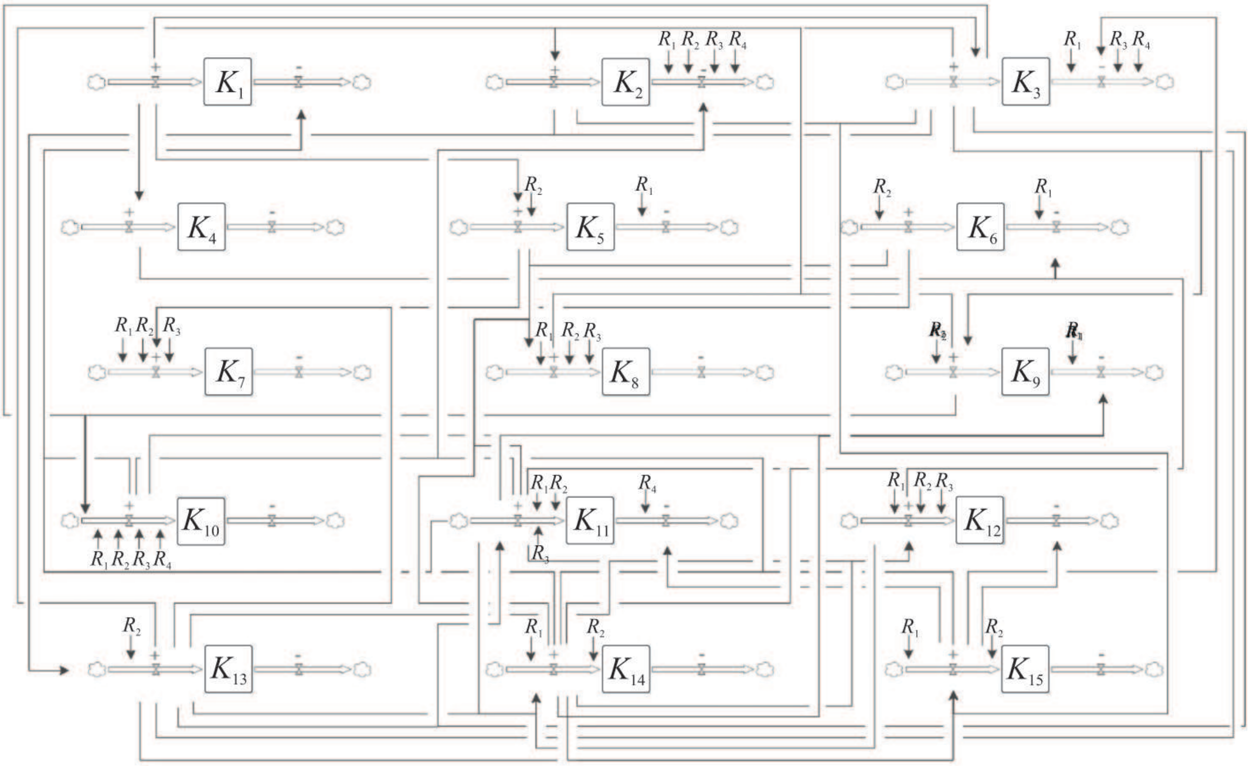

Fig. 3. Cause-and-effect graph.

Cause-and-Effect Graph between System Variables and External Influences. The cause-and-effect graph was constructed according to the methodology developed in [16, 21, 25] (see Fig. 3).

Construction of the System of System-Dynamics Equations in the General Form. Below is a part of the system of differential equations (4), describing the change of the variables $K_i(t, p(t))$, $i = \overline{1, n}$, over time, taking into account the positive and negative relationships existing between them and the influence of external factors:

$$\begin{cases} \dfrac{dK_1(t)}{dt} = -f_1(K_{10}(t)) f_2(K_{11}(t)) f_3(K_{14}(t)), \\ \dfrac{dK_2(t)}{dt} = f_4(K_3(t)) f_5(K_7(t)) f_6(K_8(t)) f_7(K_9(t)) f_8(K_{13}(t)) \\ \qquad - f_9(K_{10}(t)) f_{10}(K_{11}(t)), \\ \qquad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \\ \dfrac{dK_{14}(t)}{dt} = f_{49}(K_{11}(t)) f_{50}(K_{12}(t)) f_{51}(K_{13}(t)) \times R_1(t) + R_2(t), \\ \dfrac{dK_{15}(t)}{dt} = f_{52}(K_2(t)) f_{53}(K_3(t)) f_{54}(K_{13}(t)) f_{55}(K_{14}(t)) \times R_1(t) + R_2(t) \end{cases} \tag{4}$$

Determination of Functional Dependencies between the Model Variables. To solve system (4), it is necessary to establish the dependencies between the model variables $f_1, f_2, \dots, f_{55}$ using regression analysis, expert assessments, or the corresponding regulatory and reference documentation. When the developed models are used as part of training systems, these dependencies may also be specified at the stage of describing the scenario of the emerging critical situation.

In the article, the dependencies are approximated mainly by linear functions or second-degree polynomials possessing sufficient flexibility for modeling.

In the article, the dependencies are approximated mainly by linear functions or second-degree polynomials possessing sufficient flexibility for modeling nonlinear effects that are often present in complex systems. In addition, such polynomials can be well interpreted from the point of view of physical meaning, which makes them a convenient tool for analysis and presentation of results.

Solution of the System of Nonlinear Differential Equations. System (5), obtained after substituting into (4) the dependencies $f_1, f_2, \ldots, f_{55}$ determined at the previous stage of model development, is solved.

$$
\left\{
\begin{aligned}
\frac{dK_1(t)}{dt} &= -(0.14K_{10}^2 - 0.86K_{10} + 1.54)(0.6K_{11}^5 - 1.64K_{11} + 1.87) \\
&\quad \times(0.03K_{14}^2 - 0.03K_{14} + 0.92), \\
\frac{dK_2(t)}{dt} &= (-0.53K_3^2 + 0.34K_3 + 0.75)(-5.75K_7^2 + 3.98K_7 + 2.36) \\
&\quad \times(-7.87K_8^2 + 8K_{14} + 0.45)(-3.17K_9^2 + 5.01K_9 - 1.2) \\
&\quad \times(-14.03K_{13}^2 + 25.61K_{13} - 10.89)(-4.77K_{10}^2 - 9.69K_{10} - 5.5) \\
&\quad \times(6.47K_{11}^2 - 12.68K_{11} + 6.81)(-0.41K_{14}^2 + 0.47K_{14} + 0.64) \\
&\quad \times(13.28K_{15}^2 - 27.1K_{15} + 14.41)(0.1R_1(t) + 2) \\
&\quad \times(0.2R_2(t) + 2.5)(2\sin R_3(t) + \varphi)(4R_4(t) + 4), \\
\frac{dK_3(t)}{dt} &= (18.06K_1^2 - 35.01K_1 + 17.45)(22.81K_{15}^2 - 39.91K_{15} + 17.94) \\
&\quad \times(0.1R_1(t) + 2) + (2\sin R_3(t) + \varphi) + (4R_4(t) + 4), \\
&\ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \\
\frac{dK_{13}(t)}{dt} &= (-1.34K_2^2 + 2.13K_2 + 0.07)(-0.02K_3^2 - 0.06K_3 + 0.94) \\
&\quad \times(0.2R_2(t) + 2.5), \\
\frac{dK_{14}(t)}{dt} &= (-12.24K_{11}^2 + 21.08K_{11} - 8.38)(-3.5K_{12}^2 + 5.21K_{12} - 1.23) \\
&\quad \times(3.21K_{13}^2 - 5.21K_{13} + 2.67)(0.1R_1(t) + 2)(0.2R_2(t) + 2.5), \\
\frac{dK_{15}(t)}{dt} &= (0.67K_2^2 - 1.42K_2 + 1.6)(0.41K_3^2 - 0.4K_3 + 1) \\
&\quad \times(5.63K_{13}^2 - 10.37K_{13} + 5.67) \\
&\quad \times(0.03K_{14}^2 - 0.05K_{14} + 0.93)(0.1R_1(t) + 2)(0.2R_2(t) + 2.5).
\end{aligned}
\right. \tag{5}
$$

The initial conditions used to solve the system of nonlinear differential equations are given in Table 1.

Table 1. Initial conditions

K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}	K_{12}	K_{13}	K_{14}	K_{15}
1	1	0.43	0.91	1	1	0.94	0.94	0.65	0.71	0.73	0.48	0.85	0.53	0.84

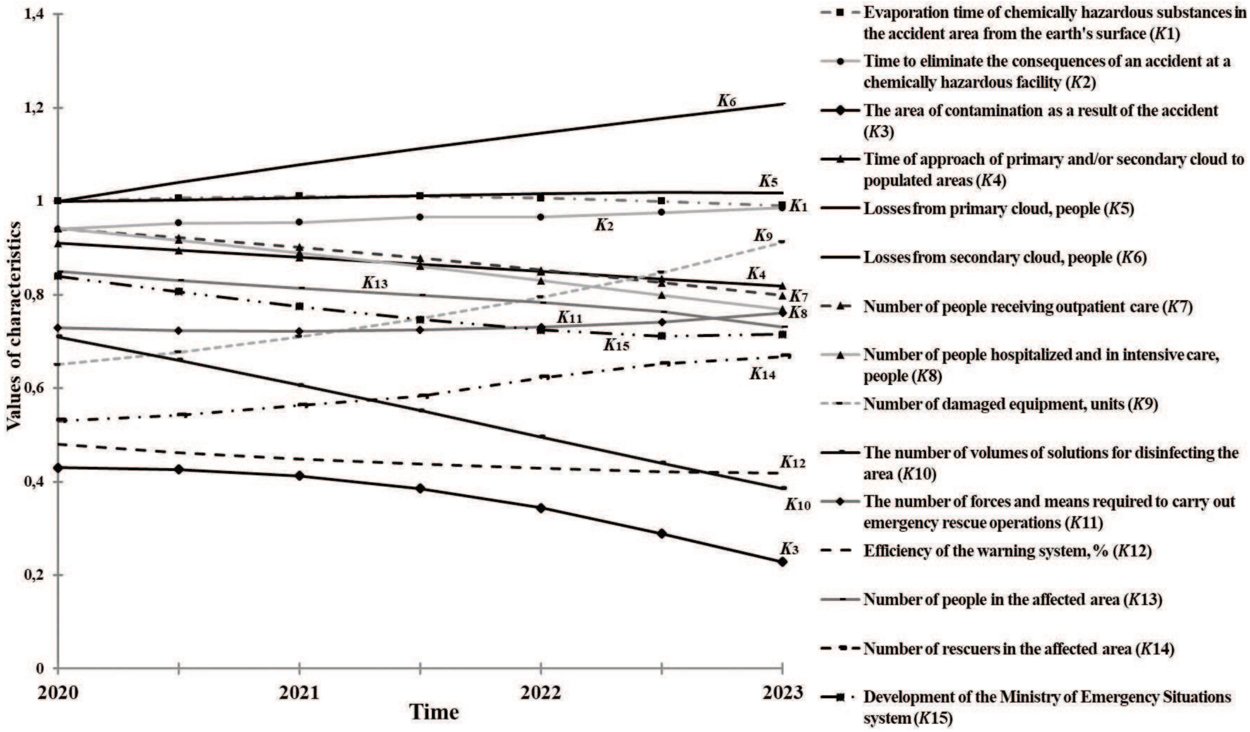

Fig. 4. Change in the normalised model variables over the machine time interval $[0; 0.6]$ of the training system.

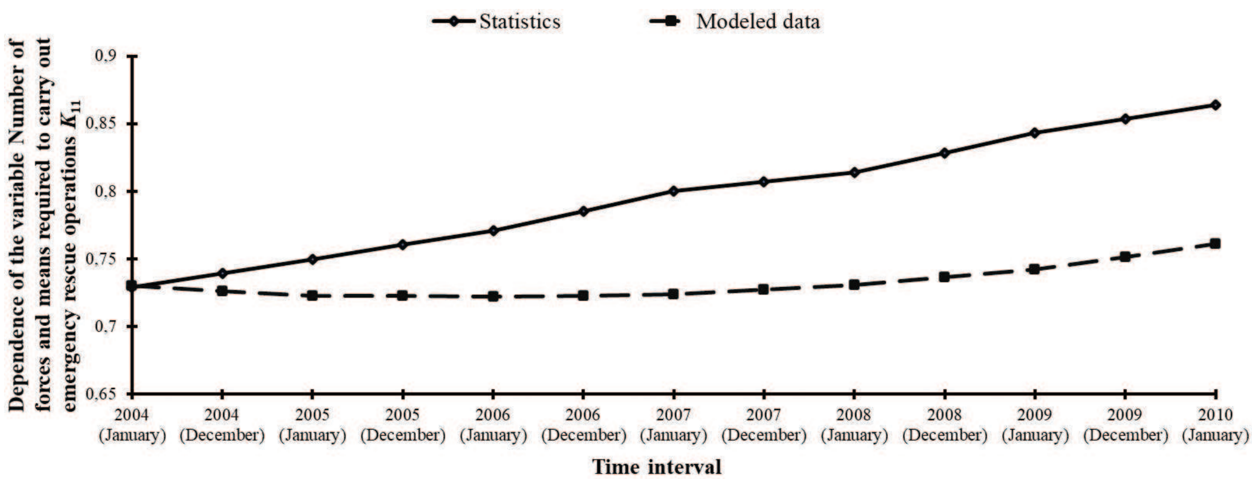

Fig. 5. Comparison of statistical and calculated data for the characteristic $K_{11}(t)$.

Figure 4 shows the graph of the normalized model variables $K_i(t, p(t))$, $i = \overline{1, n}$, obtained as a result of solving system (5).

To assess the model error, Fig. 5 presents a comparison of calculated data characterizing the change in the normalized variable $K_{11}(t)$ over the machine time interval $[0; 1.2]$ with statistical data obtained from the analysis of materials on the investigation of the explosion at the Texas City oil refinery [26].

From Fig. 5 it follows that the maximum deviation of $K_{11}(t)$ from the statistical data is 11.98%.

4. CORRECTION OF THE SYSTEM-DYNAMICS MODEL

The necessity of periodic correction of the system-dynamics model is explained by the following considerations.

Modern oil-refining and chemical enterprises are complex large-scale systems of high dimensionality, the functioning processes of which depend on many hundreds and thousands of parameters, many of which are qualitative in nature.

The development of a complete mathematical model characterizing the efficiency of the functioning of an oil refinery or a chemical enterprise is hardly possible due to the high dimensionality of the problem being solved. Moreover, such a model will have low accuracy due to the systematic accumulation of errors in determining all its numerous input variables, and the modeling error will only increase over time.

From the above, it follows that almost any mathematical model of a complex system becomes less accurate over time without periodic correction.

Below, an algorithm for correcting a system-dynamics mathematical model is presented, used in solving the problem of managing the liquidation of consequences of critical situations at oil-refining and chemical enterprises.

The algorithm makes it possible to maintain the error of the mathematical model at a specified level so that it does not affect the reliability of conclusions and recommendations formed for the decision-maker. The algorithm is based on the assumption that the accuracy of forecasting the behavior of a complex large-scale system can often be increased by reducing the forecasting interval.

Verification of the validity of this assumption should be carried out at the stage of adapting the developed mathematical support to the specific features of functioning within the control system of a particular enterprise.

At this stage, it is also necessary to determine the periodicity with which it is economically feasible and organizationally and technically possible to carry out correction of the mathematical model.

If the duration of the selected forecasting interval does not allow the required accuracy of mathematical modeling to be ensured, then the developed correction algorithm cannot be used at this oil refinery or chemical enterprise.

The presence of significant inertia in many complex large-scale systems makes it possible to conclude that the algorithm for correcting the system-dynamics model may be effective for many enterprises.

The experience of implementing the procedure for correcting system-dynamics models of large-scale systems allows one to conclude that for many oil refineries and chemical enterprises the modeling error can be maintained at a level not exceeding 10% when the forecasting interval is reduced to 12–14 months of real time, which is acceptable when solving problems (1)–(3) as part of a training complex.

Algorithm.

Step 1. Select an action plan $p_i(t) \in \{P(t)\}$ implemented during the liquidation of consequences of critical situations at oil-refining and chemical enterprises.

Step 2. Select relevant disturbances that must be taken into account when solving problems (1)–(3).

Step 3. Determine functions approximating the change of the selected disturbances over a unit time interval of machine time.

Step 4. Construct a system-dynamics model (1) in the general form.

Step 5. Determine the internal functions of the model by approximating them with low-degree polynomials $f_1, f_2, \ldots, f_{55}$.

Step 6. Present the mathematical model in a form suitable for numerical calculations by substituting $f_1, f_2, \ldots, f_{55}$ into the mathematical model (4).

Step 7. Based on statistical information, construct dependencies $K_i(t, p(t))^{\mathrm{Stat}}$, $i = \overline{1, 15}$, characterizing the change of the characteristics $K_i(t, p(t))$, $i = \overline{1, 15}$ over the time interval used in modeling within the training system.

Step 8. Solve system (5) and determine the calculated values of the characteristics $K_i(t, p(t))$, $i = \overline{1, 15}$.

Step 9. Set the value of the counter of characteristics $K_i(t, p(t))$, $i = \overline{1, 15}$ equal to one, i.e. $i = 1$.

Step 10. Compare the calculated value of the characteristic $K_i(t, p(t))$ with the value $K_i(t, p(t))^{\mathrm{Stat}}$ obtained from statistical analysis.

Step 11. If the condition

$$\forall t \in [t_0; t_N] \quad \left| K_i(t, p(t))^{\mathrm{Stat}} - K_i(t, p(t)) \right| \leqslant 0.1\, K_i(t, p(t))$$

is satisfied, i.e. if the modulus of the difference between the compared characteristics exceeds 10%, initiate the correction procedure by proceeding to the next step. Otherwise, proceed to Step 15.

Step 12. Determine the value of the correction coefficient

$$K^{\mathrm{cor}}(K_i(t, p(t))) = \frac{K_i(t, p(t))^{\mathrm{Stat}}}{K_i(t, p(t))}$$

for the characteristic $K_i(t, p(t))$ as the value by which the calculated value of the characteristic $K_i(t, p(t))$ must be multiplied in order to obtain the value of this characteristic derived from statistical analysis $K_i(t, p(t))^{\mathrm{Stat}}$.

Step 13. Modify the cause-and-effect graph G_{PSS}, the degrees, or the coefficients of the polynomials $f_1, f_2, \ldots, f_{55}$ in such a way that the condition

$$\forall t \in [t_0; t_N] \quad \left| K_i(t, p(t))^{\mathrm{Stat}} - K_i(t, p(t)) \right| < 0.1\, K_i(t, p(t))$$

is satisfied.

Step 14. Generate a message for the decision-maker on the completion of the correction operation of the main characteristic $K_i(t, p(t))$ and record in the database the value of the correction coefficient $K^{\mathrm{cor}}(K_i(t, p(t)))$.

Step 15. Increase the value of the counter of characteristics by one, i.e. assign $i = i + 1$.

Step 16. If the condition $i \leqslant 15$ holds, proceed to Step 9.

Step 17. Generate a message for the decision-maker on the completion of the correction operation of all characteristics $K_i(t, p(t))$, $i = \overline{1, 15}$, and record in the database the values of the correction coefficients of these characteristics $K^{\mathrm{cor}}(K_i(t, p(t)))$, $i = \overline{1, 15}$.

Step 18. Replace the mathematical model used before correction with a model having modified cause-and-effect relationships and coefficients of the polynomials $f_1, f_2, \ldots, f_{55}$.

End of the algorithm.

An example of correcting the model variable K_{12} over the machine time interval $[0; 1, 3]$ of the training system is shown in Fig. 6.

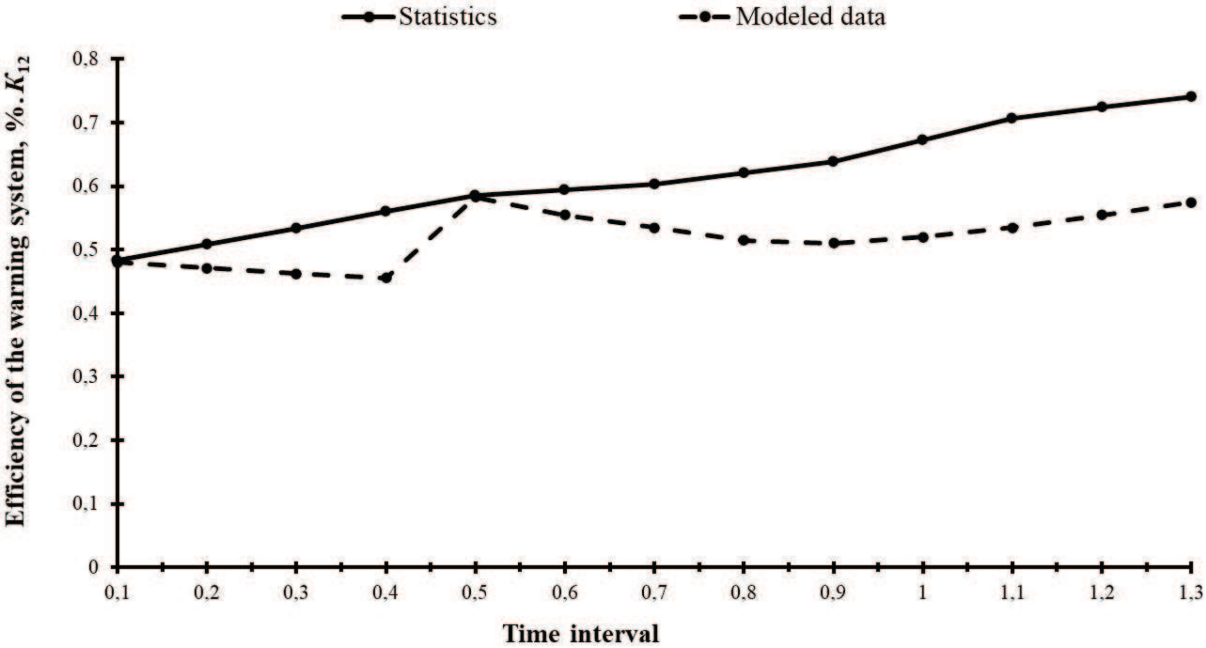

Fig. 6. Correction of the model variable K_{12} over the machine time interval $[0; 1.3]$ of the training system.

In accordance with the developed algorithm for correcting the mathematical model, correction is performed if the discrepancy between the modeling results and the statistical data exceeds 10%. Based on the data in Fig. 6, it can be concluded that over the machine time interval $[0; 1, 3]$ the model correction was performed only once at the time instant $t = 0.5$.

5. MODEL EXAMPLE

Let us consider an example of using the developed models as part of a training system intended for acquiring and improving skills in managing the processes of liquidation of consequences of critical situations at oil-refining and chemical enterprises.

Problem Statement. Suppose that accidents have occurred at an oil refinery in a large city and at a nearby chemical plant as a result of an external impact. In the training system of the facility-level unit of the Ministry of Emergency Situations, it is required to verify the feasibility of three plans for localization and liquidation of the resulting emergency situation (LLES) and to select the one that will minimize the objective function (1) subject to constraints (2) and (3).

Description of the Accident and Its Consequences. On March 23, 2005, a cloud of hydrocarbon vapors ignited and exploded at the isomerization unit of an oil refinery in Texas City (see Fig. 7). As a result, 15 workers were killed, 180 were injured, and the plant suffered severe damage amounting to \$322 million in 2024 prices. Taking into account compensation of \$2.1 billion, repair costs, production downtime, and fines, this explosion became the most costly accident at an oil refinery in the world.

Solution of the Problem. When performing model calculations, the system of differential equations (5), the initial conditions given in Table 1, and the dependencies between the model variables $f_1, f_2, \ldots, f_{55}$ determined based on the results of investigations of the largest oil refinery accident in Texas City, USA, as well as a number of accidents at domestic and foreign oil-refining and chemical enterprises [2, 4, 8, 26], were used.

Fig. 7. Consequences of the explosion at the oil refinery in Texas City.

In the model example for plans p_1–p_3, a number of model dependencies $f_1, f_2, \ldots, f_{55}$ are approximated by second-degree polynomials:

$$\begin{cases} f_{21}(K_5) = -0.144K_5^2 + 0.108K_5 + 0.98, \\ f_{22}(K_6) = -0.158K_6^2 + 0.128K_6 + 0.97, \\ f_{23}(K_{13}) = -1.85K_{13}^2 - 3.39K_{13} + 2.52, \\ f_{24}(K_{15}) = -1.54K_{15}^2 + 3.19K_{15} - 0.65. \end{cases} \tag{6}$$

To assess the approximation accuracy, the dependencies $f_7(K_8)$ and $f_{12}(K_{15})$ obtained by calculation are compared with statistical data.

In Fig. 8 and Fig. 9, the red line represents the approximation curve obtained on the basis of the polynomial model, while the black line shows real statistical data. The comparison results indicate a good agreement between the considered curves.

Substituting $f_1, f_2, \ldots, f_{55}$ into the system of equations (5), we solve this system numerically under the given initial conditions (Table 1). Substituting the obtained results into (1) in the form of dependencies $K_i(t, p(t))$, $i = \overline{1, 15}$, we calculate the value of the objective function $Z(p_1(t))$ corresponding to plan $p_1(t)$. The values of the objective function $Z(p_2(t))$ and $Z(p_3(t))$, corresponding to plans $p_2(t)$ and $p_3(t)$, are determined in a similar way (Table 2).

Table 2. Results of solving the problem.

Plans for liquidation of consequences of critical situations	$p_1(t)$	$p_2(t)$	$p_3(t)$
Value of the objective function	1.356	1.678	1.935

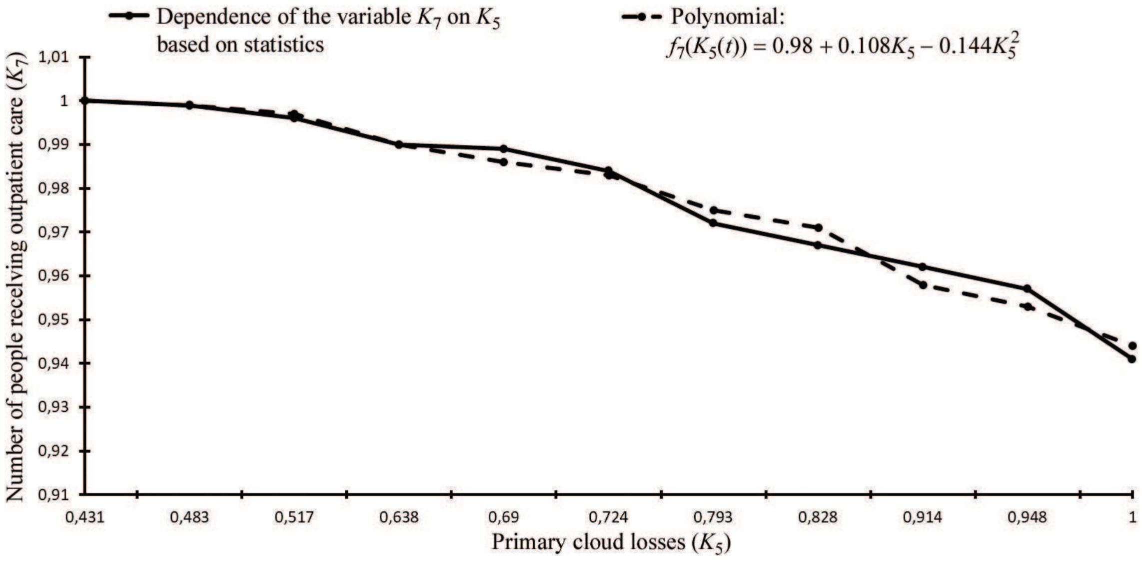

Fig. 8. Dependence of the number of people who received outpatient care (variable K_7) on losses caused by the primary cloud K_5.

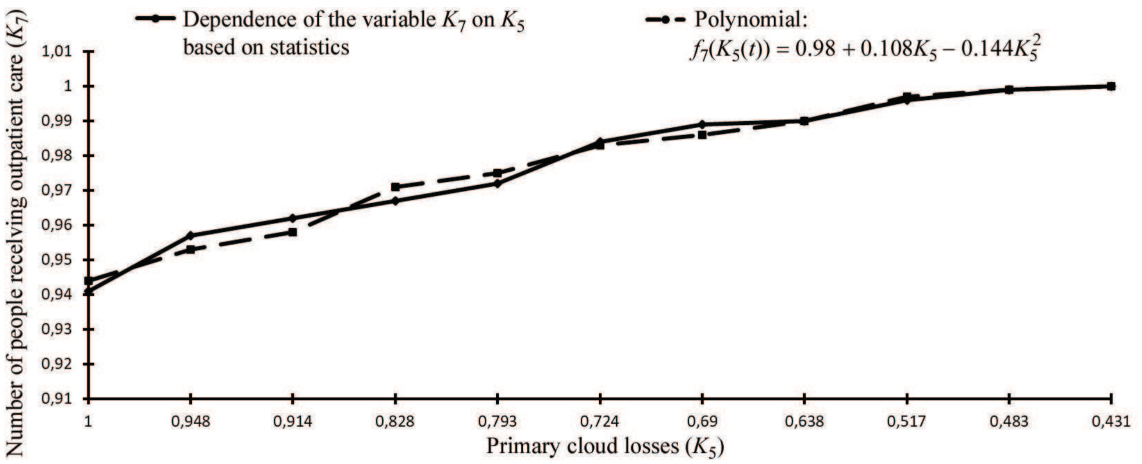

Fig. 9. Dependence of the number of people who received outpatient care (indicator K_7) on the development level of the emergency service system K_{15}.

The calculations performed show that the solution of problems (1)–(3) is the plan $p_1(t)$.

6. INFORMATION–LOGICAL SCHEME FOR SOLVING THE PROBLEM

The procedure for solving problems (1)–(3) over time intervals [minimum possible; month], [quarter; year] is presented in Fig. 10 in the form of an information–logical scheme (ILS). The scheme characterizes the main stages of minimizing damage during the liquidation of consequences of critical situations at oil-refining and chemical enterprises, the production processes of which are associated with the production, storage, and processing of toxic and potentially hazardous substances.

The following designations are used in Fig. 10: 1—technological equipment for preparing raw materials at the oil refinery; 2—equipment for primary processing of raw materials at the oil refinery; 3—equipment for secondary processing of raw materials at the oil refinery; 4—equipment for hydrotreating at the oil refinery; 5—mixing of components of finished products; 6—local automation devices; 7—recording information in the database (DB) and knowledge base (KB); 8—expert

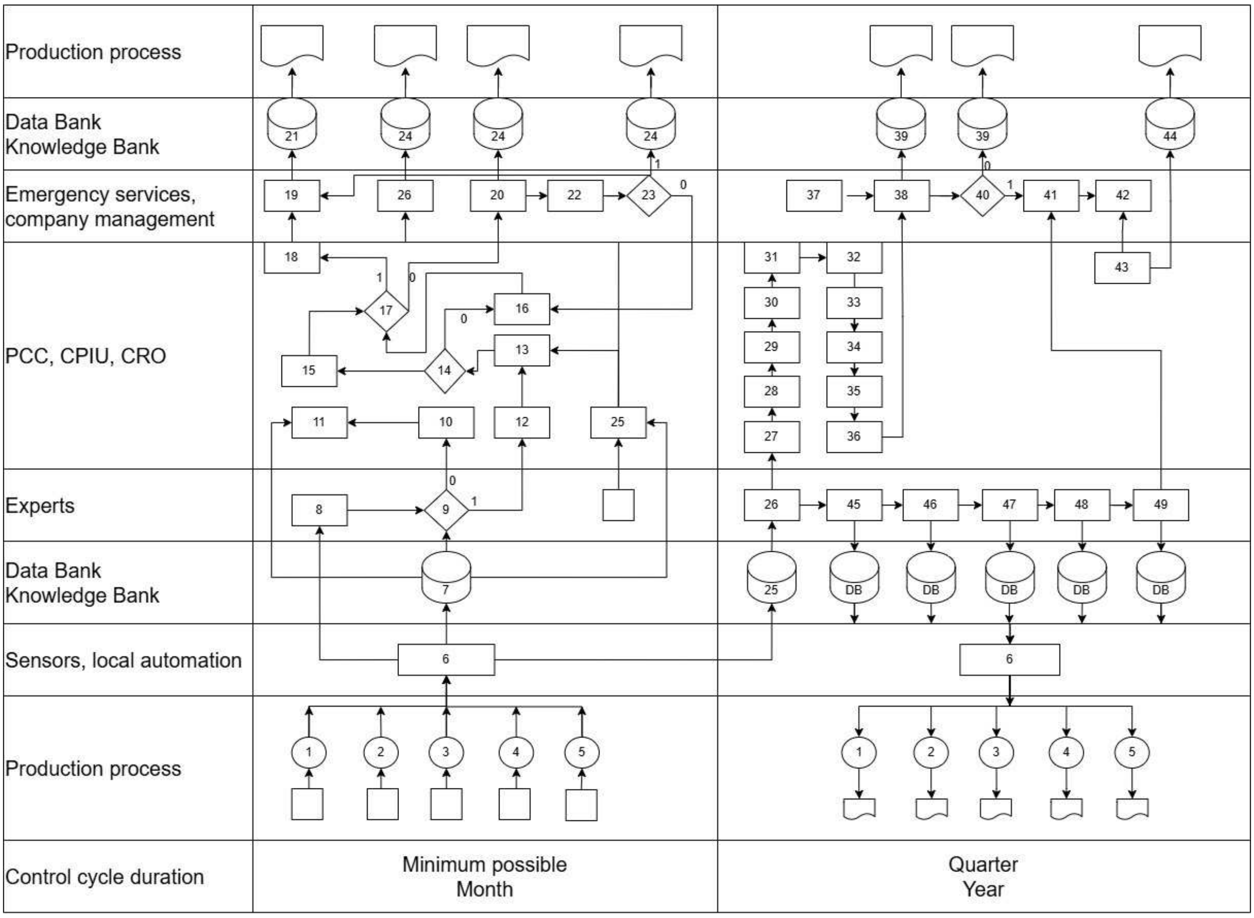

Fig. 10. Information–logical scheme for solving the problem in the system of the facility-level unit of the Ministry of Emergency Situations deployed at the enterprise [23–25].

assessment of the hazard of the emerging situation; 9—emergency situation; 10—recording information on the normal production situation in the shift dispatchers log on an electronic medium; 11—determination of measures to eliminate the normal situation; 12—collection of information on the emergency situation; 13—identification of the emergency situation; 14—for the emergency situation, plans for localization and liquidation (LLES) have been developed; 15—verification of the plans for feasibility; 16—preparation of the LLES plan; 17—is the plan feasible?; 18—notification of the feasibility of plan p_i; 19—management of plan execution p_i; 20—informing the management decision-maker about the impossibility of executing plan p_i; 21—recording in the database the results of plan execution p_i; 22—correction of plan p_i; 23—is the corrected plan p_i feasible?; 24—recording in the database information on the implemented plan p_i; 25—selection from the enterprise database of information on the release of toxic substances as a result of the accident; 26—expert assessment of the severity of the emergency situation [12, 13]; 27—determination of the mass of the toxic substance released into the atmosphere in the primary and secondary cloud; 28—determination of the concentration of the toxic substance in the affected area; 29—determination of the rise height of the toxic substance; 30—determination of the dispersion zone of the toxic substance; 31—determination of the duration of the atmospheric release; 32—determination of damage from increased morbidity of the population; 33—determination of damage to agriculture; 34—determination of damage from changes in the natural environment; 35—determination of damage due to deterioration in the quality of life; 36—determination of damage to the enterprise; 37—assessment of personnel performance efficiency; 38—informing the enterprise management and the emergency service of the facility-level unit about the calculated values of damage and personnel performance efficiency; 39—recording in the enterprise database information on the magnitude of damage caused by the atmospheric release of a toxic substance; 40—is correction of the LLES required?; 41—modification of the LLES; 42—approval of new LLES by the enterprise management; 43—training of personnel in actions for localization and liquidation of accidents using the training system; 45–49—recommendations for reducing losses specified in items 32–36 of the ILS; LLES—plan for localization and liquidation of emergency situations.

It follows from Fig. 10 that the problem of managing the liquidation of consequences of critical situations at oil-refining and chemical enterprises is solved over two time intervals of different duration: [minimum possible; month], [quarter; year].

During the solution of the problem at the first time interval, the degree of hazard of the emerging critical situation that led to atmospheric releases of pollutants is determined. The maximum size of the contamination zone by toxic or potentially hazardous substances is determined, and measures are taken to limit it and evacuate personnel. The feasibility of existing plans for localization and liquidation of emergency situations is assessed, and, if necessary, they are corrected. Information about the incident is communicated to the enterprise management and the emergency service of the facility-level unit and is also entered into the enterprise database. If necessary, the information is transmitted to the unified state system for prevention and liquidation of emergency situations.

At the second time interval, the damage caused by atmospheric emissions of pollutants is assessed; the corresponding information is entered into the database of the information system, transmitted to the enterprise management, and, in agreement with it, communicated to all interested external organizations.

7. CONCLUSION

The developed complex of system-dynamics models constitutes a tool for analysis, forecasting, and control under emergency situations, intended for use as part of information-control and training systems of oil-refining and chemical enterprises. The mathematical model, taking into account a significant number of relevant feedback relationships between the system variables, as well as external disturbing factors, makes it possible to comprehensively assess the safety of technological processes and to minimize damage during the liquidation of consequences of critical situations at oil-refining and chemical enterprises.

The use of the apparatus of regression analysis for forming functional dependencies between the internal variables of the model makes it possible to take nonlinear effects into account and to increase the accuracy of calculations. Second-degree polynomials used for data approximation made it possible to obtain the required level of calculation accuracy, while the numerical solution of the system of nonlinear differential equations provided reliable modeling results. Real statistical data served as the basis for the calculations, and their use made it possible to confirm the correspondence between the results of model calculations and statistical information.

The development of an original algorithm for correcting the system-dynamics model and for operational decision-making when variables deviate from permissible values allowed the required modeling error of approximately 10% to be ensured.

A comparison of modeling results with actual data obtained at various industrial enterprises [3] confirmed the reliability and the required level of accuracy of mathematical modeling. The results of the conducted research may serve as a basis for the further improvement of safety-management systems and risk minimization at enterprises of the oil-refining industry.

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