Розглядаються питання контролю та попередження виникненню надзвичайних ситуацій техногенного характеру. Завчасне виявлення критичних станів, точність та достовірність параметрів систем моніторингу є запорукою запобігання техногенним катастрофам різного рівня.

Запропоновано модель надзвичайної ситуації як нечіткої ситуації, що базується на теорії нечітких множин та понятті лінгвістичної змінної, визначена множина показників, які повністю описують вражаючі фактори надзвичайної ситуації. Множина показників є об'єднанням як кількісних, так і якісних даних. Показано, що запропонована нечітка модель узгоджується з характеристикам та умовами виникнення надзвичайної ситуації на об'єктах критичної інфраструктури і, в той же час, дає можливість обробки як кількісних так і якісних показників. Такий підхід дозволяє використовувати нечіткі відношення для формування груп подібності і будувати бази правил в системах підтримки прийняття рішень з урахуванням подібності ситуацій, що підвищує ефективність систем підтримки прийняття рішень.

В екстремальних умовах оперативне прийняття кваліфікованих управлінських рішень є найважливішою задачею, яка вирішується, в тому числі, за допомогою систем підтримки прийняття рішень. Оскільки для формування бази правил інтелектуальних системи необхідним є залучення експертів, в роботі запропоновано метод представлення та обробки експертних даних, що дозволяє визначити характеристики їх узгодженості і обрати відповідний метод обробки. Запропоновані підходи до моделювання надзвичайних ситуацій дозволять проводити ідентифікацію ситуацій з метою контролю, попередження та формуванні комплексу дій у випадку настання надзвичайної ситуації, що дозволить зберегти людські життя та природні ресурси

Ключові слова: надзвичайна ситуація, нечітка ситуація, експертна інформація, системи підтримки прийняття рішень

THE MODELS OF ANTHROPOGENIC EMERGENCIES FOR DECISION SUPPORT SYSTEMS

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1. Introduction

The development of technologies to ensure the safety of critical infrastructure, especially in emergencies, is an important component of the state's economy and security. Any emergencies of natural and anthropogenic nature can cause significant material damage, lead to the environment and human sacrifices [1]. Water pollution, which may accompany such emergencies, violates the standards set by the International Federation of Red Cross and Red Crescent Societies [2]. Especially devastating for the environment are the accidents at such high-risk objects as enterprises in the chemical, metallurgical, petroleum, and other industries. The result of anthropogenic disasters at such objects is a sudden failure of machines, mechanisms, and assemblies during operation. It is accompanied by serious disruptions in the production process, explosions, the formation of fire sites, radioactive, chemical, or biological contamination of large areas, the damage and loss of life [3]. The major accidents in the chemical industry are relatively rare, but the damage to workers, the loss of property, business interruption, as well as harm to the environment, are very serious [4]. According to data from the

Swiss Re Institute [5], 304 disasters occurred in 2018, similar to those that occurred in 2017. Of those, 181 were natural disasters (184 in 2017); 123 – anthropogenic catastrophes. The overall economic damage from natural and anthropogenic disasters in 2019 amounted to about USD 140 billion against USD 176 billion in 2018. Natural disasters intensified due to the imbalance of the environment; in some cases, it is indirectly related to human activities [6].

Emergencies are characterized by the complexity of prediction, sudden occurrence, the rate of propagation, incomplete and uncertain initial information, the nature of consequences depends on a particular situation, and has a chain character. The advance detection of emergency events (EE), the accuracy and reliability of monitoring system parameters is the key to the prevention of anthropogenic disasters of different levels. Operators play a decisive role during emergencies in different organizations. When abnormalities occur in a production process, an operator is often pressed for time to correct or evacuate before the situation becomes fatal [7]. Alarm systems play an important role in the industry to notify operators about an abnormal situation. There is a problem of false signals and missed signals at actual enterprises, which

hinders the operator's judgment when making a decision [8]. If an extraordinary event arises, it can turn into a variety of possible emergencies due to the dynamic peculiarities of emergency events. Before deciding, a decision-making person should collect all the information (possible situations, possible losses caused by various possible situations, etc.). In a real situation, given inadequate or incomplete information, especially in the early stages of an emergency, the decision-making person can hardly assess all factors and make an adequate decision [9]. The current automated systems are for the most part either monitoring systems or simulate an EE propagation, or aimed at evacuation activities in an emergency. That is why it is a relevant task to develop an intelligent decision support system (DSS) for the detection and prevention of emergencies and for supporting operative decision-making in case of an emergency event under conditions of unreliable or incomplete data. The development of decision-making systems requires the construction of appropriate mathematical models of subject domains, control objects, taking into consideration the experience of elimination and the necessary activities under EE conditions.

2. Literature review and problem statement

The development of effective monitoring systems and DSS implies the simulation of all stages and should include control over the technological process indicators, the setting of parameters in the emergence of an alarming situation, modeling the propagation, as well as activities, in case of an emergency. Paper [8] notes that the preassigned alarm values, the order of the dynamic alarm, and the alarm algorithm are the three main elements in the system of alert and alarm. The authors proposed a strategy of signal optimization; however, the issue of incomplete information arising under such conditions is not considered.

In order to solve various decision-making tasks in an emergency, study [9] suggests using a perspective-based method for assessing alternatives. Given the existing decision-making methods, based on the perspective method, the ideal alternative is usually the one that has the largest common perspective value. However, in the real world, a perfect alternative is not sometimes optimal for eliminating an emergency as there are many other factors to consider during the selection of alternatives, for example, the cost of an alternative, the number of resources to respond to emergencies, etc. Therefore, there is an issue to make an alternative close to an actual situation.

Work [10] proposed using, for modeling EE, virtual reality, immersive and interactive technologies. However, the study is limited to designing the simulators for personnel training in emergencies.

Papers [11–13] address modeling an EE considering its spatial and temporal component. In work [11], the simulation takes place under an assumption that EEs happen within the limited territorial system only. Since the subject area of the cited work is an EE of natural character, the authors assume several sites of its occurrence. No situations of anthropogenic character were explored. Study [12] addresses the EEs at transportation, associated with the threat of explosions. A theoretical-set approach is used for modeling, in combination with the producing models at the known EE parameters. However, under actual conditions, it is not always possible to define all parameters. In work [13],

the model of EE elimination is built on the assumption that the information about an emergency is deterministic; an emergency has n simultaneously existing factors of hazard. The model employs statistical categories such as relative frequency and mathematical expectation. At the same time, constraints in the observation of EE, the inadequate accuracy of measuring the environmental parameters complicates the application of statistical approaches [11].

Even though there are different models, none of them is generally accepted. Paper [14] suggests, in order to prevent and predict emergencies or failures of systems, to use the models of cause and effect leading to EEs. The authors pay attention to the security principles of the system and analyze the causes of accidents, but there is no emergency model. It is noted that in order to detect relationships and influence of hidden factors, as well as to identify systematic violations, it is advisable to involve experts whose knowledge and experience is the basis to build a database and a rule base for intelligent decision support systems.

An expert often analyzes the situation in general, analyzing the decisions that were taken earlier in similar situations [15]. He/she then either directly applies these decisions or, if necessary, adapts them to the circumstances that have changed for a particular problem. The simulation of this approach to solving problems, based on the experience of past situations, resulted in the emergence of a logical inference technology, based on precedents [15]. In some situations, the inference method based on precedents demonstrates serious advantages over a conclusion based on rules but, at the same time, there are two issues: a search for the most relevant precedents and subsequent adaptation of the found decision.

The methods for modeling and manipulating a knowledge base, underlying intelligent DSS, can be grouped based on 4 categories:
1) a base of linguistic knowledge;
2) a base of expert knowledge;
3) ontology;
4) a base of cognitive knowledge [16].

Part of the findings of that study was to establish a strong dependence of the linguistic knowledge base, experts' knowledge base, and ontology, on the unstable expert knowledge. At the same time, the problem of eliminating the instability of expert knowledge was not considered.

One option to solve it is to use an averaged expert assessment based on the weighted average significance of the estimates given by the experts [17]. The proposed approach could be used in the case when the derived results of processing the expert information are represented in the form that can be treated by statistical methods, which poses a problem when the values are qualitative or fuzzy.

Our analysis of the literary sources has revealed that existing models for solving the tasks of decision support in an emergency are mainly reduced to modeling the processes of the elimination of consequences and propagation of EEs within a territory, actions of personnel in an emergency. The issues related to analyzing those parameters that describe hazardous factors, and methods of their processing taking into consideration the unreliable and incomplete characteristics of the information, have not been considered. At the same time, a given issue is important when detecting an EE and in the formation of qualified managerial decisions about appropriate activities associated with its occurrence.

The task of building an EE model is solved mainly from the point of view of constructing the spatially oriented

models taking into consideration the timeline component. At the same time, controlling the condition of an object and further identification of a probable EE, as well as decision making in emergencies, requires its identification based on the parameters of hazardous factors. The setting of parameters of a dangerous situation is important. The statistical methods of an EE description have constraints on their application for solving the set task. The issue of processing expert knowledge has not been resolved.

3. The aim and objectives of the study

The aim of this study is to simulate an EE of anthropogenic character under conditions of fuzzy and incomplete data, with the use of expert information, in order to construct the decision support systems based on them.

To accomplish the aim, the following tasks have been set:
– to decompose the problem of preventing EEs and to build mathematical models of EEs, defining the hazardous factors related to emergencies;
– to construct a method to process expert information considering the fuzzy character of the data;
– to implement the proposed models and methods numerically.

4. Construction of the mathematical model of an emergency to determine hazardous factors

The prevention of anthropogenic accidents is a complex scientific and practical task. A set of issues constituting a part of this problem includes the following:
– analysis of the experience of previous emergencies;
– forecasting and modeling of emergencies at each potentially dangerous facility;
– control and evaluation of licensing conditions involving the activity and rendering of services related to hazardous substances;
– compilation and evaluation of production plans in the case of emergency: emergency and rescue operations, evacuation, etc.;
– the construction of mathematical models for modeling and analyzing EEs;
– the design and implementation of intelligent automated decision support systems for emergencies;
– the development and implementation of effective response, monitoring, and alerting systems in the case of emergency;
– the implementation of measures aimed at preventing accidents during the production and transportation of hazardous substances;
– training of personnel and population for activities in the case of emergency;
– analysis and modeling of risks associated with the use of hazardous substances.

Let us represent a mathematical notation of each hazardous factor in the case of an emergency.

Let $Y=\{y_1, y_2, ..., y_p\}$ be the set of features whose values set an EE. In this case, the values of the factors can be determined both based on regulatory data and with the involvement of experts. In this case, if the estimates by an expert are qualitative, then, to describe the links, one uses the relations of a linear and partial order, equivalence of tolerance, or any

relations that do not possess such properties as connectedness, transitivity, etc.

Each y_i attribute, describing EE, can be characterized as follows:
– $w(y_i)$ – the hazardous influence of factor y_i takes the value «low», «below medium», «medium», «above average», «high»; experts estimate the influence in the interval $[0;1]$ – at $w(y_i)=0$, we have a zero hazardous influence; at $w(y_i)=1$, the factor y_i exerts maximum influence on EE;
– $v(y_i)$ – the significance of factor y_i to identify an EE; it takes the value «not important», «importance below average», «average importance», «importance above average», «high importance»; experts estimate the influence in the interval $[0;1]$: $v(y_i)=0$ – the factor can be ignored at identification, but there is the influence of factor y_i on EE; $v(y_i)=1$ the maximum significance for EE identification;
– $int(y_i); int(y_i) \in [\underline{int}_i; \overline{int}_i]$ – the factor y_i intensity, $\underline{int}_i$ – the minimum value of the indicator, $\overline{int}_i$ – the maximum (critical) indicator value;
– $q_1(y_i), ..., q_n(y_i)$ – other parameters of the y_i factor.

Given the above notations, the mathematical model y_i of an EE attribute can be recorded as an n-dimensional vector (1):

$$y_i = \begin{Bmatrix} w(y_i), v(y_i), int(y_i), \\ q_1(y_i), ..., q_n(y_i) \end{Bmatrix}. \tag{1}$$

The values $w(y_i), v(y_i)$ are determined by experts based on previous experience. Such data require the development of procedures for the fuzzification and defuzzification. The $int(y_i)$ parameter is determined by means of sensors, including gas analyzers. The $\underline{int}_i$, $\overline{int}_i$ parameters are determined both as the fixed indicators on the basis of normative documents and are calculated by the specified procedures. Thus, according to the resolution of the Cabinet of Ministers of Ukraine [18], a threshold mass depends on the smallest distance from the elements of a potentially dangerous object to the elements of the residential area or industrial objects. If it does not exceed 500 meters for hazardous substances of groups 1 and 2 and 1,000 meters for hazardous substances of group 3, the threshold mass of hazardous substances is determined from the following formula (2):

$$Q_{ir} = Q_i * (R_X / R_P)^2, \tag{2}$$

where Q_{ir} is the threshold mass of a hazardous substance, Q_i is the calculated or computed threshold mass according to Order for class 2, R_X is the distance from a potentially dangerous object to the boundary of the nearest element in a residential area or industrial object, R_P is the limit distance from a potentially dangerous object to the nearest industrial object or an element in a residential area, from which the norm of the threshold mass is recalculated (for substances from groups 1 and 2, it is equal to 500 meters, for group 3 substances, R equals 1,000 meters).

When Q_{ir} is less than 1 percent than the threshold mass set or calculated according to the Order for class 2, the threshold mass is taken equal to 1 percent irrespective of the distance from a potentially dangerous object to the elements in a residential area.

Given the fuzzy nature of the data, we shall represent each emergency as a fuzzy situation.

Let $Y = \{y_1, y_2, ..., y_p\}$ be the set of features whose values set an EE. A set of attributes should be constructed by experts for each type of EE. When modeling a system of control

and prevention at a chemical enterprise, the set of attributes can include the territory of possible destruction, material losses, depreciation of the equipment, etc., which are characterized by such fuzzy concepts as a large zone of destruction, average wear, etc. The fuzzy attributes $y_i (i \in I = \{1,...,p\})$ are assigned by the corresponding linguistic variable $\langle y_i, \mathrm{T}_i, D_i \rangle$, where $T_i = \{T_1^i, T_2^i, ..., T_{m_i}^i\}$ is the term-set of a linguistic variable (a set of the linguistic values of an attribute), m_i is the number of terms, D_i is the basic set of the y_i attribute. To describe the terms $T_j^i (j \in L = \{1, 2, ..., m_i\})$, which correspond to the values of the y_i attribute, we use fuzzy variables $\langle T_j^i, D_i, \tilde{C}_j^i \rangle$, that is, a T_j^i value is characterized by a fuzzy set $\tilde{C}_j^i$ in the base set D_i [19]:

$$\tilde{C}_j^i = \{< \mu_C(d)/d >\}, \quad d \in D. \tag{3}$$

Thus, in terms of the theory of fuzzy sets, each EE $\tilde{s}$ can be considered as a fuzzy set of the second level (4):

$$\tilde{s} = \{< \mu_s(y_i)/y_i >\}, \quad y_i \in Y, \tag{4}$$

where $\mu_s(y_i) = \{< \mu_{\mu s}(T_j^i)/T_j^i >\}, \quad T_j^i \in T_i.$

Using this approach makes it possible to create a model of the situation that would take into consideration both the attributes, which are described in fuzzy terms and the quantitative characteristics. Taking into consideration the above notation, the identification of fuzzy situations can be performed with the help of fuzzy inclusion, fuzzy equation, and fuzzy similarity of situations. This will make it possible to form methods of control, common for each class, to prevent an emergency and, in the case of its occurrence, to choose necessary measures for its elimination.

In terms of fuzzy logic, an *EE* is determined by the following term-set of values for a linguistic variable: *EE*= =\{«safe situation», «unstable situation», «average threat», «critical situation», «dangerous situation»\}.

Building the membership functions for each fuzzy set and determining the base set requires a unified approach as the fuzzy logic system should be used for any EEs. That is why we shall consider the interval $X=[0;1]$ as the base set. Denote via α_Σ the operator to convert a set of fuzzy attributes $y_i (i \in I\{1,...,p\})$ to number $k \in [0;1]$, which characterizes the degree of danger of a certain situation: $\alpha_\Sigma : Y \rightarrow [0;1]$.

Since the EE monitoring system is a real-time system, control over the EE parameters can be executed both discretely and under a continuous mode. State the conditions of control using the following expression (5):

$$\forall t_i, t_{i+1}[T_0, T_n] : EE(t_{i+1}) - EE(t_i) \leq k_{kr}, \tag{5}$$

where t_i, t_{i+1} are the control measurement points; $[T_0, T_n]$ is the period of control, $EE(t_{i+1})$, $EE(t_i)$ is the status of the situation at time points t_{i+1}, t_i.

In this case, the state of a control object $SO(t)$ at time t takes the form specified by expression (4):

$$\forall t \in [T_o; T_n], \quad SO(t) = G(\Delta S(t/t_0), \{\hat{y}_i\}, f(t)), \tag{6}$$

where G is the operator of the control object description, $\Delta S(t/t_0)$ is the function of change in the state of a control object at time t_i compared to the initial state at time t_0, $\{\hat{y}_i\} \in Y$, $Y = \{y_1, y_2, ... y_p\}$ is the set of features whose values set an EE, $f_{SO}(t)$ is the function of the object's state control.

Given the specificity of the subject area under consideration and the need to engage experts in the formation of a rule base for the IDSS and the formation of a system of state control rules, it is necessary to use the methods to process expert information. In this case, expert opinions can be both consistent and inconsistent.

5. A method to process expert opinions

Consider the issue of processing expert knowledge. Let there be n experts $X = \{x_i\} = \{x_1, x_2, ..., x_n\}$. The experts are asked to estimate the set $A = \{a_j\} = \{a_1, a_2, ..., a_m\}$ of alternatives by determining them using the values from the term-set $T^j = \{a_1^j, a_2^j, ..., a_{kj}^j\}$.

Determine the optimal set of linguistic values for alternatives as follows. Let there be, as regards the alternative a_j, a term-set $T_i^j = \{t_{i1}^j, t_{i2}^j, ..., t_{ikj}^j\}$ of linguistic values formulated by expert x_i. Then $T^j = \bigcap T_i^j$, $i = 1, ..., n$. An expert, in this case, assigns the number μ from the interval $[0; 1]$, which characterizes the degree of conformity between the alternative a_j and the selected term t_k^j. In this case, we get a discrete membership function, built by a direct method. Experts' opinions, in this case, may coincide or be inconsistent. Accordingly, the methods to process expert data are chosen. We shall use the method, proposed in [20], to describe the alternatives and determine the consistency of data provided by experts.

Merge the opinions by experts, obtained in line with the procedure described above, for each alternative a_j, into the matrix $n \times k_j$.

$$\mathbf{M}_{jT^j}^i = \begin{array}{c|cccc} & t_1^j & t_2^j & ... & t_{k_j}^j \\ \hline x_1 & \mu_1^1(a_j) & \mu_2^1(a_j) & ... & \mu_k^1(a_j) \\ x_2 & \mu_1^2(a_j) & \mu_2^2(a_j) & ... & \mu_k^2(a_j) \\ ... & ... & ... & ... & ... \\ x_n & \mu_1^n(a_j) & \mu_2^n(a_j) & ... & \mu_k^n(a_j) \end{array}, \tag{7}$$

where $x_1, ..., x_n$ are the experts, t_k^j is the term, $\mu_k^i(a_j)$ is the membership function.

Denote $\mu_k^i(a_j) = \mu_{jk}^i$ the value of a membership function of the alternative a_j to the term t_k^j according to the opinion by the x_i-th expert.

Under such an approach, it is necessary to consider the competence of experts. To address this issue, we shall use the frequency of unmistakable expert assessments based on statistical data. Let the expert x_i participated in N expert assessments, and in M of them, his/her results were true. Then the weight of the x_i-th expert is denoted via $w(x_i) = M/N$, in this case, $0 \leq w_i \leq 1$.

Thus, in accordance with fuzzy algebra, each alternative will be set by the following expression:

$$a_j = (T^j, \mu_T(a_j), w^j), \tag{8}$$

where a_j is the alternative, T^j is the term-set of linguistic values for the alternative a_j, $\mu_T(a_j)$ is the set of membership functions, w^j is the average weight of expert opinion in relation to the alternative a_j.

We introduce several conditions for expression (7):

$$\exists k' : k \leq k' \leq k_j, \quad \sum_{i=1}^n \mu_{jk'}^i \neq 0, \quad \sum_{i=1}^n \mu_{jk}^i = 0, \quad k \neq k', \tag{9}$$

$$\exists t_k^j : \max_{i,h} \left(\mu_{jk}^i - \mu_{jk}^h \right) \le 0.5. \qquad (10)$$

By mapping the estimates onto the axis (μ, T), we receive the well-grouped opinions if the membership functions have a single clustering center. In this case, we call the assessment of experts coherent. If under the same conditions, there are several centers, the assessment of experts shall be called conditionally coherent. The space built above is termed the expert space and is denoted by A_n^m, each point of which a_i^j, the estimation given by the x_i-th expert to the a_j-th alternative, is described by a vector.

To rank the alternatives, we represent the experts' information, provided by the x_i-th expert, in the form of a matrix $A(x_i)$:

$$\left(E_i \right) = \begin{array}{c|cccc} & t_1 & t_2 & ... & t_k \\ \hline a_1 & \mu_{11} & \mu_{12} & ... & \mu_{1k} \\ a_2 & \mu_{21} & \mu_{22} & ... & \mu_{2k} \\ ... & ... & ... & ... & ... \\ a_n & \mu_{n1} & \mu_{n2} & ... & \mu_{nk} \end{array}, \qquad (11)$$

where μ_{ij} is the membership function of the a_i-th alternative to the t_j-th term.

Introduce a quantity $p_j(a_i)$ – the occurrence frequency of alternative a_i.

Arrange the alternatives in the following way. r_i denotes the rating of the alternative a_i, which is determined according to the number of terms, for which the membership function of the considered alternative accepts a maximum value. That is, the maximum rating r_1 belongs to the alternative for which $r_1 = a_i \cdot a_i : p_i = \max_i p(a_i)$.

The alternatives whose ranking was determined are eliminated from the consideration. The sequence, derived by using the proposed method, makes it possible to arrange alternative variants of activities in the case of emergency taking into consideration all factors that characterize the alternatives. The proposed method of expert information processing can be applied both for the coordinated and uncoordinated opinion of experts as it is based on the comprehensive data assessment and takes into consideration the competence of experts.

6. Numerical implementation of the proposed models of emergencies and methods for processing fuzzy expert data

Consider the numerical implementation of the models and methods constructed in our study.

Build a vector that characterizes the y_i factor's hazardous influence using ammonia as an example. In this case, $w(y_i))$ is the function of $int(y_i)$, where $w(y_i)$ and $int(y_i)$ are directly interdependent: the higher $int(y_i)$, the higher $w(y_i)$. The importance of factor $v(y_i)$ is determined by experts, the intensity of $\underline{int}(y_i)$ is determined by means of sensors-gas analyzers, $\underline{int}_i = 0$, $\overline{int}_i$ is the threshold (explosive) concentration in the air, from 15 to 28 % (107...200 mg/l). Other parameters include:

– $q_1(y_i)$ – the threshold weight of class 1 dangerous substance, which is equal to 500 t;

– $q_2(y_i)$ – the threshold mass of class 2 dangerous substance, 50 t;

– $q_3(y_i) = \{1, 8\}$ – the categories to which a substance can be attributed;

– $q_4(y_i) = \{1, 3\}$ – the groups to which a substance can be attributed. The groups categorize the hazardous substances based on the types of accidents, which can occur on the basis of the properties of hazardous substances, and based on the influence of hazardous factors of these accidents;

– $q_5(y_i) = 1$ – the toxicity of a substance ($q_5(y_i) = 1$ if the substance is toxic, $q_5(y_i) = 0$ otherwise);

– $q_6(y_i) = 4$ – class 4 hazard;

– $q_7(y_i) \approx 0.45$ MPa (4.5 kgf/cm^2) – the maximum explosion pressure of an ammonia-air mixture;

– $q_8(y_i) = 0.0028$ % (0.02 mg/l) – the maximum permissible volume of ammonia in the working area;

– $q_9(y_i) = 0,035$ % (0.25 mg/l) – the maximum permissible volume of ammonia in the air, which does not cause consequences after being exposed for 60 min, $q_9(y_i)$ [0.05 %; 0.1 %] ([0.35 mg/l; 0.7 mg/l]) – the maximum permissible volume of ammonia in the air, life-threatening;

– $q_{10}(y_i) = [0.21$ %; 0.39 %] ([1.5 mg/l; 2.7 mg/l]) – the maximum permissible volume of ammonia in the air, which causes lethal effect when exposed for 30...60 minutes.

The above indicators that characterize the hazardous effect of ammonia in the case of emergency are, according to (1), the coordinates of a threshold value vector.

According to expressions (5), (6), control over the state of a control object must be executed taking into consideration the indicators of hazardous factors in $Y = \{y_1, y_2, ..., y_p\}$ – the set of attributes whose values set an EE.

Thus, the totality of factors that describe an emergency can be represented as a combination of quantitative and qualitative assessments, some indicators may not be available, which is the cause of incomplete and fuzzy data. This fact predetermines using the elements of fuzzy logic and fuzzy sets in modeling and forecasting EEs.

We shall numerically verify the method of expert data processing. Suppose a survey implies four experts $X = \{x_1, x_2, E_3, x_4\}$, who assess six alternatives $A = \{a_j\} = \{a_1, a_2, ..., a_6\}$, by determining their membership functions for terms $T = \{t_1, t_2, ..., t_6\}$. Assume $w(x_1) = 0.8$, $w(x_2) = 0.6$, $w(x_3) = 0.8$, $w(x_4) = 0.7$. The alternatives are the options of activities in the case of emergency, the terms are the cost of an alternative, the amount of resources for responding to emergencies, etc. In this case, we assume that the terms $T = \{t_1, t_2, ..., t_6\}$ are arranged in descending order of priority.

Based on expression (11), we form the alternatives and values for the terms' membership functions in a matrix $A(x_1), ..., A(x_4)$, which correspond to the opinions by four experts.

$A(x_1) =$	t_1	t_2	t_3	t_4	t_5	t_6
a_1	0.5	0.6	0.7	0.8	0	0.1
a_2	0.4	0.2	0	0.3	0	0.4
a_3	0.1	0.5	0	0.2	0.9	0.6
a_4	0	0.1	0.9	0.3	0.2	0.5
a_5	0.7	0.2	0.2	0.3	0.4	0.7
a_6	0.1	0.9	0.4	0.3	0.8	0.6

$A(x_2) =$	t_1	t_2	t_3	t_4	t_5	t_6
a_1	0.4	0.4	0.6	0.9	0.1	0.05
a_2	0.3	0.3	0.1	0.2	0.2	0.4
a_3	0.05	0.3	0.2	0.2	0.8	0.5
a_4	0.1	0.1	0.8	0.3	0.25	0.4
a_5	0.8	0.2	0.2	0.4	0.5	0.7
a_6	0.15	0.9	0.5	0.4	0.8	0.7

$$A(x_3) = \begin{array}{c|cccccc} & t_1 & t_2 & t_3 & t_4 & t_5 & t_6 \\ \hline a_1 & 0.6 & 0.5 & 0.75 & 0.7 & 0.05 & 0.15 \\ a_2 & 0.4 & 0.3 & 0 & 0.3 & 0.1 & 0.3 \\ a_3 & 0.1 & 0.4 & 0.1 & 0.3 & 0.8 & 0.6 \\ a_4 & 0 & 0.1 & 0.9 & 0.3 & 0.2 & 0.5 \\ a_5 & 0.7 & 0.2 & 0.2 & 0.6 & 0.4 & 0.7 \\ a_6 & 0.1 & 0.9 & 0.4 & 0.5 & 0.8 & 0.6 \end{array}$$

$$A(x_4) = \begin{array}{c|cccccc} & t_1 & t_2 & t_3 & t_4 & t_5 & t_6 \\ \hline a_1 & 0.4 & 0.5 & 0.5 & 0.8 & 0.1 & 0.1 \\ a_2 & 0.3 & 0.2 & 0.1 & 0.2 & 0.2 & 0.4 \\ a_3 & 0.05 & 0.5 & 0.1 & 0.25 & 0.9 & 0.5 \\ a_4 & 0.1 & 0.1 & 0.8 & 0.3 & 0.3 & 0.4 \\ a_5 & 0.8 & 0.2 & 0.2 & 0.4 & 0.5 & 0.7 \\ a_6 & 0.2 & 0.9 & 0.5 & 0.4 & 0.8 & 0.7 \end{array}$$

Process the expert information received from the first expert. Perform ranking for each value of the set's term, by ordering the alternatives based on a decrease in the value of the corresponding membership function. The resulting sequences are summarized in Table 1.

Table 1

The sequences of alternatives, arranged in accordance with the values of a membership function for the first expert

Term	Alternatives				
t_1:	a_5	a_1	a_2	$<a_3, a_6>$	a_4
t_2:	a_6	a_1	a_3	$<a_2, a_5>$	a_4
t_3:	a_4	a_1	a_6	a_5	$<a_2, a_3>$
t_4:	a_1	$<a_2, a_4, a_5, a_6>$	a_3		
t_5:	a_3	a_6	a_5	a_4	$<a_2, a_1>$
t_6:	a_5	$<a_6, a_3>$	a_4	a_2	a_1

The occurrence frequency of alternatives is given in matrix $P(x_1)$.

$$P(x_1) = \begin{array}{c|ccccc} & p_1(a_i) & p_2(a_i) & p_3(a_i) & p_4(a_i) & p_5(a_i) \\ \hline a_1 & 1/6 & 3/6 & 0 & 0 & 2/6 \\ a_2 & 0 & 1/6 & 1/6 & 2/6 & 2/6 \\ a_3 & 1/6 & 1/6 & 2/6 & 1/6 & 1/6 \\ a_4 & 1/6 & 1/6 & 1/6 & 1/6 & 2/6 \\ a_5 & 2/6 & 1/6 & 1/6 & 2/6 & 0 \\ a_6 & 1/6 & 6/6 & 1/6 & 1/6 & 0 \end{array}$$

Taking into consideration the technique to construct the $P(x_1)$ matrix and by analyzing the obtained data, one can conclude that the strongest alternative is a_5, since its relative frequency is the greatest. In terms of the assumptions made, this means that it is the best for two terms and, accordingly, its ranking is the largest. In the second column, the alternatives a_1 and a_6 take the same values of relative frequencies and, consequently, these alternatives for three terms accept the value of a membership function, following the maximum value, and, for a single term, take a maximum value. However, $p_3(a_6)=1/6$, $p_3(a_1)=0$. Therefore, a_6 has the advantage and ranks second. Following a similar analysis of all columns, we obtain the following ranking of the alternatives based on the

results from processing the data provided by the first expert: $a_5, a_6, a_1, a_3, a_2, a_4$.

Perform a similar procedure for $A(x_2)$. The results from analyzing the alternatives are given in Table 2.

Table 2

The sequences of alternatives, arranged in accordance with the values of a membership function for the first expert

Term	Alternatives					
t_1:	a_5	a_1	a_2	a_6	a_4	a_3
t_2:	a_6	a_1	$<a_2, a_3>$	a_5	a_4	
t_3:	a_4	a_1	a_6	$<a_3, a_5>$	a_2	
t_4:	a_1	$<a_5, a_6>$	a_4	$<a_2, a_3>$		
t_5:	$< a_6, a_3>$	a_5	a_4	a_2	a_1	
t_6:	$<a_6, a_5>$	a_3	$< a_2, a_4>$	a_1		

The occurrence frequencies are shown in matrix $P(x_2)$.

$$P(x_1) = \begin{array}{c|cccccc} & p_1(a_i) & p_2(a_i) & p_3(a_i) & p_4(a_i) & p_5(a_i) & p_6(a_i) \\ \hline a_1 & 1/6 & 3/6 & 0 & 1/6 & 1/6 & 0 \\ a_2 & 0 & 0 & 3/6 & 2/6 & 1/6 & 0 \\ a_3 & 1/6 & 1/6 & 1/6 & 2/6 & 0 & 1/6 \\ a_4 & 1/6 & 0 & 3/6 & 0 & 2/6 & 0 \\ a_5 & 2/6 & 2/6 & 0 & 2/6 & 0 & 0 \\ a_6 & 3/6 & 1/6 & 1/6 & 1/6 & 0 & 0 \end{array}$$

After analyzing all the columns, we obtain the following ranking of the alternatives based on the results from processing the data provided by the second expert: $a_6, a_1, a_2, a_4, a_3, a_5$.

Similarly, based on the data processing results, we obtain the following ranking for the third expert: $a_5, a_6, a_1, a_4, a_2, a_3$, for the fourth: $a_6, a_1, a_5, a_2, a_4, a_3$.

Given the weight of each expert, the resulting alternatives are ranked in the following way: $a_5, a_6, a_1, a_4, a_2, a_3$. The alternatives are arranged according to a sequence scale.

7. Discussion of EE modeling results

The proposed a model of an *EE* in the form of a fuzzy situation using the representation of an attribute in the form of vector (1) taking into consideration a hazardous factor is substantiated by several reasons. Firstly, the representation of an anthropogenic situation in the form of a fuzzy situation is predetermined by the presence of the attributes defined by the qualitative indicators, as well as a high probability of the incomplete information regarding the control processes. Secondly, the use of an *n*-dimensional vector as a model of the EE attributes is predetermined by the characteristics of hazardous factors. To prevent accidents, a prerequisite is the advance detection of deviations from the normative or permissible parameters. The comprehensive control, in accordance with (5), (6), can be executed based on the comparison of coordinates of the actual state's vectors, as well as a control vector, whose coordinates are the thresholds of the parameters of the controlled processes. This approach makes it possible to comprehensively characterize the processes being dealt with and to identify a situation based on the hazardous factors. Owing to the representation of an EE in the form of

a fuzzy situation (3), (4), we avoided the problems that arise when the statistical methods are used to simulate an EE. Using a model of the fuzzy situation makes it possible to apply, in order to identify an EE, the relations of fuzzy similarities and fuzzy inclusion. By determining the measure of a situation similarity in this way solves the task of finding the most relevant precedents, which is the advantage compared to the approach suggested in [11]. A possibility to apply the similarity relations to the proposed models makes it possible to make decisions even under the condition of incomplete data, which removes the constraints that exist in works [12, 13]. Thus, further studies should be aimed at building such relations in the subject area under consideration.

The method of processing expert data based on the concepts of fuzzy logic, reported in this paper, is consistent with the mathematical representation of an emergency in the form of a fuzzy situation. This method can be used both for the formulation of individual EE attributes and for ranking the alternatives in decision-making. The application of expressions (7) to (10) makes it possible to evaluate the consistency of experts' opinions. Based on processing the data, compiled in matrix (10), regarding expert opinions, we can rank the alternatives. Note that the use of fuzzy models to represent alternatives with further data processing based on the values of membership functions eliminates discrepancies in expert estimates and resolves the issues related to the statistical approaches outlined in [16, 17]. The introduction of an experts' competence coefficient allows adjusting the conclusions depending on the experts' experience. It should be noted that the proposed approach makes it possible to take into consideration all the criteria by which an alternative could be assessed. This is achieved by generating a term set for each alternative. The evaluation of alternatives based on these criteria with their subsequent ranking makes it possible to solve the problem of bringing the alternative selection to actual, which is the advantage over the methods given in [9]. However, a given approach has a limitation as it is necessary to have information about previous experience to determine the qualification of an expert, and it is proper for a person not to advertise his/her mistakes. In addition, this method ignores the issue of ranking the term set of linguistic values: the cost of an alternative, the amount of resources, and how they relate to possible losses, etc.

The numerical implementation of the proposed approaches confirms the possibility of using the developed methods and models in real situations. Thus, the data from Tables 1, 2 demonstrate a technique to construct a sequence of alternatives based on a decrease in the value of a membership function and make it possible to track the degree at which any alternative dominates others. This principle is the basis of ranking alternatives by a sequence scale. However, the task of obtaining the values for membership functions is not considered in this method. It should be noted that in order to process large arrays of information for the proposed approach, it is necessary to use appropriate software.

8. Conclusions

1. We have constructed mathematical models that are based on combining the theory of fuzzy sets and the theoretical-set approaches, which make it possible to represent a situation in a combination of both the numerical parameters and linguistic values. Such a representation, in contrast to representing a situation in the form of clear sets based on quantitative parameters only, makes it possible to identify situations and to make decisions under conditions of incomplete information. The specified task is solved through a possibility to apply to such models the measures of situation similarities. This, in turn, greatly simplifies the construction of a rule base to identify the situations and make decisions. The proposed model for representing an EE attribute is an n-dimensional vector. The coordinates are the characteristics of hazardous factors that were formed based on the normative indicators, monitoring systems, expert information. Such an approach, combined with the representation of a situation using fuzzy models, has made it possible to comprehensively represent the object of control and to take into consideration all the factors that describe it.

2. A method of expert information processing has been suggested, which makes it possible to assess the consistency of experts' opinions and to solve the task of ranking the alternatives. It has been shown that such a method enables the construction of a term-set of alternatives, taking into consideration all the factors that exist in an alternative selection. The principle of forming the terms sequence and the algorithm for ranking the alternatives in accordance with the values of membership functions makes it possible to form an alternative choice as close to the real situation. The proposed algorithm for ranking the alternatives by a sequence scale enables the application, if a better alternative cannot be used, of the second-best in terms of priority.

3. The numerical verification of the proposed methods and models has shown the possibility of their application to actual industrial objects. The numerical implementation of a fuzzy expert data processing method has confirmed the suitability of the proposed approach to processing both consistent and inconsistent data.

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