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RISK ASSESSMENT IN EMERGENCY SITUATIONS USING A BAYESIAN NETWORK

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***Abstract*—*The article presents a comprehensive analysis of modern approaches to risk assessment in emergency situations, with a focus on fire-related incidents. It reviews both qualitative and quantitative methods, including expert-based assessments, Monte Carlo simulations, decision trees, FMEA, FTA, and HAZOP. Special attention is given to bayesian networks as a dynamic tool for probabilistic modeling. The proposed method allows for the integration of prior knowledge with new data and provides updated risk estimates in real time. A bayesian network structure was developed to model the impact of various environmental and operational factors on key risk indicators, such as human casualties, material losses, and environmental damage. A simulation scenario demonstrates the system's ability to adapt to changing inputs and support informed decision-making. The results confirm the effectiveness of bayesian networks in emergency risk analysis, especially when data is incomplete and decisions must be made quickly.*

Keywords—emergency management; fire risk assessment; Bayesian network; probabilistic modeling; decision support; risk analysis; dynamic systems; hazard prediction.

I. INTRODUCTION

In the first half of 2024, the Institute of Public Administration and Research in Civil Protection conducted an analysis of the fire situation in Ukraine. The analysis was based on data provided by regional departments of the State Emergency Service of Ukraine (SES), in accordance with the Instruction on Fire Reporting approved by Order No. 445 from August 16, 2017, and its amendments (Order No. NS-109 from February 7, 2023) [1].

During the reporting period, 34.493 fire incidents were registered in Ukraine, showing a 46.1% increase compared to the same period in 2023. The main reason for this growth was a significant rise in the number of fires in open areas – a 2.2 times increase - which now account for 57.1% of all fires.

As a result of these fires, 730 people died, including 17 children, and 758 people were injured, among them 50 children. While the overall number of deaths decreased by 5.1%, the number of injuries increased by 11.3%. Child mortality decreased by 22.7%, and injuries among minors (under 18) decreased by 29.6%.

The total material damage caused by fires was estimated at 28.57 billion UAH, with direct losses amounting to 13.04 billion UAH and indirect losses to 15.53 billion UAH [1].

Modern fire monitoring systems use various sensors (temperature, smoke, flame) combined with algorithmic solutions that allow real-time data analysis [2]. Much attention is given to evacuation route planning using graph algorithms, which take into account blocked areas and fire zones [3].

Besides evacuation, another important issue is the optimal allocation of resources among emergency response units. When real-time data is available - such as the fire location, fire size, and the number of people in the building – intelligent systems can quickly determine the required number of fire units, the type of equipment, and the best mobilization strategy [2].

II. RISK ASSESSMENT METHODS

One of the key components of a modern fire protection system is a comprehensive risk assessment. It helps to define the level of potential danger and forms the basis for making informed decisions about necessary response actions. Depending on the purpose of the analysis, the availability of data, and the required level of detail, various approaches are used in risk management practice – from qualitative to quantitative.

Qualitative risk analysis is usually applied at the early stages of the assessment process or in situations where there is not enough quantitative data. This approach is mainly based on expert judgments and provides a descriptive classification of threats according to their probability and potential impact. Within the framework of qualitative analysis, expert survey methods, such as the Delphi method, are widely used, as well as tools like formalized risk matrices. These matrices allow certain risks to be classified into specific categories (for example, "low," "medium," "high") based on approximate estimates of the likelihood of an event and the severity of its consequences. The main advantages of the qualitative approach are its speed, clarity, and the possibility to use it when information is limited. At the same time, its disadvantages include a high degree of subjectivity, since the results largely depend on the level of expert competence, agreement between specialists, and the quality of available descriptive data [4].

The Monte Carlo method belongs to the class of quantitative risk analysis methods that take into account the uncertainty of future events by performing multiple simulations of possible scenarios using random variations of input parameters. Each system parameter is assigned a corresponding probability distribution (for example, normal, triangular, log-normal, etc.), and then a large number of simulations is performed – often hundreds of thousands or even millions of iterations. This makes it possible to obtain a complete picture of the statistical distribution of outcomes, assess the level of risk within different confidence intervals, and identify both the most likely and extreme (worst-case) scenarios. The advantage of this method is its ability to model complex stochastic systems. However, to ensure the reliability of the results, it is critically important to choose the correct type of probability distribution for the input variables and to have sufficient computing power [5].

Decision tree analysis is an effective analytical method used to compare alternative strategic options, taking into account the probabilities of possible events and the corresponding expected outcomes, including benefits or losses. During the construction of a decision tree, each branch represents a specific decision or stochastic outcome, while the final nodes (so-called "leaves") show the expected consequences, including financial flows, potential losses, or other quantitative indicators. The calculations are performed by computing the expected value for each scenario, which helps to choose the optimal option according to rational criteria. Despite its visual clarity and ease of use at the beginning, the method quickly becomes more complicated as the number of decision options, probabilistic transitions, and interdependencies increases, which limits its application in highly complex structures [6].

Bayesian networks (BNs) are powerful modeling tools that allow analysts to formalize and visualize cause-and-effect relationships between multiple random variables, and also dynamically update risk estimates as new data becomes available, following Bayes' theorem. In such a network, each node corresponds to a certain variable with defined probabilistic characteristics, while the influence directions between variables are represented by arcs. A key part of this approach is the conditional probability tables (CPTs), which make it possible to adjust initial assumptions by updating probability distributions when new information appears. This approach is especially valuable in situations with high uncertainty, where constant updating of predictions and decisions based on available empirical data is necessary [7].

The FMEA method (Failure Mode and Effects Analysis) is a widely recognized tool in manufacturing and technical fields, where reliability indicators of equipment and the safety of technological processes are extremely important. The main goal of this method is to identify potential failures of components or systems and to perform a detailed analysis of each of them by examining causes, likelihood, consequences for the system as a whole, and the possibility of timely detection. As a result of the analysis, a numerical risk priority number (RPN) is calculated, which is then used to decide the order in which risk-reduction measures should be implemented to improve the overall effectiveness of the system [8].

The Fault Tree Analysis (FTA) method is a systematic approach to reliability and safety analysis. It focuses on identifying and visualizing the cause-and-effect chains that may lead to critical or undesired events. In this method, a graphical structure is created in the form of a "tree," where the top event usually represents a system failure or another risk outcome. From this point, branches grow upward, consisting of chains of logical elements that describe the combination of events, conditions, or technical failures that can lead to this event. Each branch is formalized using logical operators (AND, OR), which allows accurate modeling of the interdependencies between components. The method not only helps to trace the entire chain of potential failures but also makes it possible to conduct quantitative probability analysis of individual scenarios, identify critical components, and prioritize actions to improve overall system safety. This method is especially useful for analyzing complex engineering systems, where the interaction of many components may become a source of serious technological threats [9].

The HAZOP method (Hazard and Operability Study) is a formalized technique for identifying potential hazards and operability issues. It is widely used in the chemical, petrochemical, and other high-risk industries. The main concept of the method is structured team-based analysis of a technological process or equipment. The expert group uses a specific set of guide words (such as “more,” “less,” “none,” “opposite”) in combination with process parameters to identify possible deviations from normal operation. During the analysis, the team examines the possible causes of each deviation, its likely consequences, and the existing or required control measures. This structured approach allows the identification of threats that could lead to accidents, failures, or reduced process efficiency. The result is a list of recommendations for eliminating identified hazards, which improves the overall level of safety and operational reliability of the system [10].

Scenario planning is a strategic analysis tool used for modeling and assessing several possible future developments. This approach is especially relevant in highly dynamic and uncertain environments, where accurate forecasting is difficult or impossible. Within scenario planning, several scenarios are developed - from a baseline scenario, considered the most probable, to alternative ones that are based on different assumptions about the pace of technological development, macroeconomic trends, or changes in regulatory policies. Each scenario undergoes a comprehensive risk assessment, which helps identify the system’s vulnerabilities and develop adaptive strategies that consider possible changes in the external environment [11].

III. Problem Statement

In the previous section, a number of risk assessment methods were reviewed, including qualitative expert approaches, the Monte Carlo method, decision trees, FMEA, FTA, HAZOP, and others. Although these methods are effective in certain situations, they also have several significant limitations. In particular, qualitative approaches are characterized by a high level of subjectivity and do not always allow for consideration of dynamic changes during emergency situations. The Monte Carlo method and decision trees, although they provide quantitative evaluation, require a large volume of input data and predefined scenarios, which reduces their flexibility in real time. Methodologies such as FTA and HAZOP, although powerful in the context of technical analysis, are mostly based on static modeling and do not take into account the possibility of updating data during the development of events

In this regard, there is a need for an approach that combines the ability to formally represent cause-and-effect dependencies between risk factors with dynamic updating of estimates in response to changes in input data. One of these tools is the bayesian network (BN), which allows the calculation of probabilities for different types of risks (for example, “explosion risk,” “human casualty risk”), adapting estimates when new information becomes available. This approach enables the implementation of a flexible decision support system in real time, which is especially important in emergency situations.

It is proposed to use a BN as the basis for such probabilistic modeling, as it provides a transparent scheme for combining prior knowledge with updated observations while also taking into account the interdependencies between factors.

The task addressed in this study is to create a risk assessment system for fire events based on a Bayesian network. To do this, a set of factors is introduced:

$$F = \{F_1, F_2, \ldots, F_i, \ldots, F_n\}, \qquad (1)$$

where each element F_i characterizes a certain aspect of the environment or the object in an emergency situation (for example, type of building, presence of water supply sources, distance to fire response units, building density, etc.).

Based on the processing of this set of factors, a risk vector is formed:

$$R = (R_1, R_2, \ldots, R_j, \ldots, R_m), \qquad (2)$$

where each component R_j corresponds to a specific type of potential threat (for example, risk to people, risk of structural collapse, risk of fire spreading, etc.).

It is necessary to construct a mapping function:

$$\Phi : F \to R, \qquad (3)$$

which allows, given a set of factors F, the estimation of the corresponding risks R, and which, in turn, serves as the basis for making operational and strategic decisions in the field of fire response.

IV. Approach to Fire Risk Estimation

A bayesian network is a directed acyclic graph:

$$G = (V, E), \qquad (4)$$

where V is a set of nodes, each representing a specific feature or factor of the situation (for example, “presence of smoke”), and E is a set of edges that show causal or conditional dependencies between these features.

One of the key advantages of BNs is the ability to factorize the joint probability distribution function for the entire set of variables. This means that the joint probability of an event:

$$P(v_i, v_2, \ldots, V_n) = \prod_{1}^{n} v_i \mid \text{parent}(v_i), \tag{5}$$

where parents(v_i) is the set of parent nodes for node v_i.

This structure avoids the need to store a full joint probability table, which would otherwise require exponential space. Instead, the probabilities are defined separately for each node, which greatly simplifies both expert configuration and network training based on empirical data.

The process of building a BN for the task of risk estimation in the event of a fire can be conditionally divided into several stages.

Step 1. Identifying factors and features

At the first stage, a set of variables is defined that describe both the initial situation and the possible consequences of the emergency. For modeling purposes, it is advisable to divide these variables into three groups.

- *Input factors* – such as the type of building, distance to the nearest fire station, percentage of triggered smoke detectors, etc. These nodes usually have no parent nodes and are characterized by prior probability distributions.
- *Intermediate (derived) factors* – include, for example, the probability of an explosion, the speed of fire spread, the number of people in the building, availability of evacuation routes, etc. These are derived from one or more input factors and may have complex interrelationships with each other.
- *Output risk indicators* – such as the risk of human casualties, level of material damage, and probability of environmental harm. These nodes are located at the end of the causal chain and depend on the entire preceding structure.

All variables in the model are subject to discretization – for example, using categories such as “low,” “medium,” or “high” level.

Step 2. Constructing the graph

At this stage, each factor or indicator becomes a separate node in the network. Based on expert knowledge, causal relationships between the nodes are determined, allowing for the construction of a directed acyclic graph. It is important to avoid cycles, as they would violate the dependency hierarchy in the BN.

Step 3. Defining probability distributions

For each node without parents, a prior probability distribution is defined. For nodes with parents, a Conditional Probability Table (CPT) is constructed - either based on statistical data or expert estimation. This structure allows flexible adaptation of the model to the available data.

Step 4. Updating probabilities

When new information becomes available (for example, activation of additional sensors or updated data about the building), the BN automatically updates probability estimates using Bayes’ theorem. For instance, if the node “Presence of flammable substances in the building” has a causal relationship with the node “Risk of rapid ignition,” then an increase in the probability of the former will automatically influence the risk estimation of the latter, in accordance with the corresponding CPT.

As a result, the system dynamically generates an updated risk assessment, which can be used to support real-time decision-making during emergency response.

V. RESULTS OF MODELING

To model the fire risk assessment process using a BN, three types of nodes were defined. These nodes represent different levels of influence within the structure of causal relationships.

Input factors are initial variables that are not affected by other network elements. This group includes such parameters as the type of building, the percentage of triggered smoke detectors, and the distance to the nearest fire station. These variables serve as the foundation for further estimates within the network.

Intermediate (derived) factors include variables that may depend on one or more input factors. These are, in particular, the presence of explosive substances, the number of people in the building, the probability of an explosion, and the probability of rapid fire spread. These variables mediate the influence of primary environmental characteristics on potential consequences.

Output nodes are the final risk indicators that require assessment within the model. These include the risk of human casualties, risk of material losses, and risk of environmental pollution. The values of these variables are determined by the combined influence of the preceding layers of the network.

Figure 1 presents the structural scheme of the BN for the fire risk assessment task. The graph illustrates the relationships between key factors and features of the situation that affect the development of the event and its probable consequences. This approach allows for a formal analysis of complex emergency scenarios, adaptation of risk estimates to new data, and the provision of evidence-based decision support in real time.

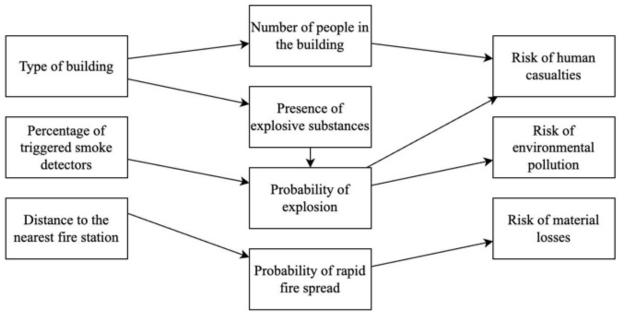

Fig. 1. Graph of the Bayesian Network

For the practical modeling of situations involving the outbreak of a fire, a set of discretized variables was developed and used in the BN structure. Each variable is represented by specific value categories that reflect typical conditions of high fire hazard facilities:

- type of building – {shopping mall, warehouse, factory};
- percentage of triggered smoke detectors – {0%, 1–30%, 31–70%, more than 70%};
- distance to the nearest fire station – {less than 3 km, 3–10 km, more than 10 km};
- presence of explosive substances – {yes, no};
- number of people in the building – {fewer than 100, 100–500, 500–1500, more than 1500};
- probability of explosion – {low, medium, high};
- probability of rapid fire spread – {low, medium, high};
- risk of human casualties – {low, medium, high};
- risk of material losses – {minor, moderate, critical};
- risk of environmental pollution – {none, local, significant}.

For modeling purposes, the following scenario was chosen: the emergency response system receives a fire alarm signal from a warehouse. The system uses geoinformation data to determine the distance to the nearest fire station and submits this data, together with the type of building and the percentage of triggered smoke detectors, as input to the model.

In this demonstration scenario, it is assumed that the emergency response system receives a signal indicating the activation of the fire alarm at a warehouse. Using the geoinformation subsystem, the system automatically determines the distance to the nearest fire station, as well as the percentage of activated smoke detectors, as reported by the sensor network. Based on these initial factors, the system initializes the corresponding nodes in the BN.

In this case, the following input parameters are recorded:

- type of building: warehouse;
- percentage of triggered smoke detectors: 1–30%;
- distance to the nearest fire station: 3–10 km.

These values are entered into the model as prior data. Then, using the probability propagation mechanism (inference), the system evaluates all model nodes, including the output risk indicators. The risk estimates for this scenario are shown in Table I.

TABLE I. RISKS AFTER INITIAL SMOKE DETECTOR ACTIVATION

Risk	Low	Medium	High
Human casualties	64%	29%	6%
Material losses	46%	34%	20%
Environmental pollution	54%	29%	17%

After receiving additional information about the possible presence of explosive materials in the warehouse, the probability of explosion in the model was adjusted from “low” to “medium.” As a result, the system updated the probability estimates of each BN node in accordance with the new input data, which affected the calculated indicators of overall risk. The detailed results of this updated modeling are shown in Table II.

TABLE II. RISKS AFTER UPDATING EXPLOSION PROBABILITY

Risk	Low	Medium	High
Human casualties	62%	32%	6%
Material losses	44%	34%	22%
Environmental pollution	25%	40%	34%

The modeling results presented in Tables I and II demonstrate the sensitivity of the risk assessment to changes in input factors within the BN. In the initial scenario, when the system registers only a fire at the warehouse with a low level of smoke detector activation (1–30%) and a medium distance to the fire station (3–10 km), the risk of human casualties is mostly low (64%), with only 6% falling into the high-risk category. A similar pattern is seen for material losses (minor – 46%) and environmental pollution (none or local – 54%).

After receiving additional information regarding the possible presence of explosive substances in the building, the explosion risk was revised from low to medium. This change caused an automatic update of probabilities in all related nodes of the network, according to conditional dependencies. For example, the low risk level of environmental pollution dropped significantly (from 54% to 25%), while the high risk category increased to 34%. This indicates a strong dependence of environmental consequences on explosion probability, which in turn is influenced by other environmental factors.

These changes demonstrate the advantages of BNs in terms of flexible model adaptation to new real-time data. Thanks to the probability propagation mechanism, it becomes possible to promptly refine threat estimates and make better-informed management decisions. The decrease in the "low" risk share across all categories after updating the data suggests an increased overall danger level, and also shows the effectiveness of the model as a tool for decision support in dynamic environments.

Thus, the modeling results confirm the feasibility of using BNs for risk assessment in emergency situations, especially fires. This approach not only allows for formal consideration of a wide range of interrelated factors but also adapts forecasts based on new information, which is critically important under crisis conditions.

VI. Conclusions

This article reviewed modern approaches to risk assessment in emergency situations, especially in the case of fires, with a special focus on the potential use of BNs as a tool for formal and dynamic modeling. The analysis shows the advantages of this approach compared to traditional methods such as FMEA, decision trees, or Monte Carlo simulations, especially in the context of real-time decision-making, incomplete data, and the need to update forecasts during ongoing events.

The BN model developed in this study allows for the inclusion of dependencies between multiple risk factors, flexible adaptation to new information, and accurate estimation of potential threats - such as the risk of human casualties, material damage, and environmental pollution. The demonstration scenario confirmed that even a slight update in input parameters can significantly change the distribution of risks. This highlights the importance of integrating such models into decision support systems.

Therefore, the implementation of BNs in the practice of emergency management can significantly increase the effectiveness of risk assessment, improve the timeliness of response actions, and enhance the justification of managerial decisions, helping to reduce the consequences of fires and raise the overall safety level of the population.

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В. М. Синєглазов, Ю. А. Кот. Оцінювання ризиків у разі надзвичайних ситуацій з використанням Баєсової мережі

У статті представлено всебічний аналіз сучасних підходів до оцінки ризиків у надзвичайних ситуаціях, з акцентом на випадки, пов’язані з пожежами. Розглянуто як якісні, так і кількісні методи, зокрема експертні оцінки, моделювання Монте-Карло, дерева рішень, FMEA, FTA та HAZOP. Особливу увагу приділено використанню баєсових мереж як динамічного інструменту ймовірнісного моделювання. Запропонований підхід дозволяє інтегрувати апріорні знання з новими даними та забезпечує оновлення оцінок ризиків у режимі реального часу. Побудовано структуру баєсової мережі для моделювання впливу різних середовищних та експлуатаційних факторів на ключові індикатори ризику, такі як людські втрати, матеріальні збитки та екологічна шкода. Симуляційний сценарій демонструє здатність системи адаптуватися до змінних вхідних даних та підтримувати обґрунтоване прийняття рішень. Результати підтверджують ефективність використання баєсових мереж в аналізі ризиків під час надзвичайних ситуацій, особливо в умовах неповноти даних і потреби у швидкому реагуванні.

Ключові слова: управління надзвичайними ситуаціями; оцінювання ризику пожежі; Баєсова мережа; ймовірнісне моделювання; система підтримки рішень; аналіз ризику; динамічні системи; прогнозування небезпек.

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