Predicting Fire Risk in High-Risk Facilities Using Risk Estimation Algorithms

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Abstract: This article considers the issue of using algorithms for calculation of estimates in ensuring fire safety at high-fire risk facilities. The proposed algorithms are based on methods and approaches such as multi-criteria assessment and statistical analysis. According to the assessment results, facilities are rated according to the level of danger and optimal management decisions are developed for fire prevention measures. The possibilities of fire risk monitoring and prediction are also considered. As a result of the research, an algorithmic solution has been developed that helps digitize the decision-making process aimed at increasing the level of safety for high-fire risk facilities. This approach allows reducing fire risk, minimizing errors caused by the human factor, and effectively planning safety measures. However, in this article, mathematical models and statistical analysis methods are used to assess fire risk, and the accuracy of predictions is increased through the integration of artificial intelligence with machine learning algorithms. According to the results, the developed model allows for early detection of dangerous situations in high-risk facilities and increases the efficiency of security systems. Using the proposed algorithms, an index expressing the risk level in percentages is formed, which facilitates the categorization of facilities by risk level. The results of this study will be of practical importance in the field of fire safety for the modernization of monitoring systems, optimization of the activities of firefighting services, and planning preventive measures.

1 INTRODUCTION

In today's era of globalization, with the expansion of industry, transport, logistics and energy sectors, the risk of fire is also increasing. Especially in production facilities, warehouses, chemical industry enterprises and crowded places where flammable materials are used, the probability of fire is high. According to statistics, the economic damage caused by fires and the threat to human health are increasing every year. Therefore, the issue of ensuring fire safety is relevant not only in production processes, but also in social infrastructure.

Traditional assessment methods are often based on subjective opinion and do not allow for a complete determination of the level of fire risk. A modern approach requires the use of assessment systems based on algorithmic calculations and data analysis. With the help of algorithms for calculation of estimates, it is possible to assess the level of fire risk of objects based on specific indicators, divide them into categories and make decisions on ensuring fire safety. This approach also allows for real-time monitoring, efficient resource allocation, and fire prevention through the identification of high-risk areas.

Therefore, the development and implementation of algorithms for calculation of estimates is an important step in improving fire safety. The increasing material and moral damage caused by emergencies in the world, the need for scientific research on the development of traditional and modern methods of intelligent processing of information in digital systems, new approaches, is emerging. In particular, great attention is paid to the theoretical and practical improvement of various models and methods of intelligent data analysis and machine learning. In this regard, scientific research is being conducted in the world to solve the problem of identifying patterns based on algorithms for calculation of estimates, including the development of model algorithms and databases and software packages for initial processing of primary information based on regression analysis [1], [2].

2 METHODS AND RESULTS

Today, there are many modified versions of the partial precedence algorithm, and in the process of improving it, it is important to introduce additional parameters into it or to optimally select parameter values. One way to modify the partial precedence algorithm is to select a subset of a small number of reference objects and recognize control objects with this subset of reference objects. Selecting a subset of reference objects provides a number of advantages: it increases the quality of recognition by cleaning the training sample from interference objects; it reduces the machine time for implementation by identifying similar objects when recognizing control objects. This approach plays an important role in recognizing large amounts of data; it forms a reduced and optimal representation of the training sample. The objects remaining in the subset of reference objects are considered as representatives of the class. It should be noted that removing some objects from the training set does not mean losing information; this process continues until the training set is fully formed.

Most methods for pattern recognition use a training set of objects, not all of them, but a certain subset of them. A vivid example of this is Vapnik's “Support Vector Machines” (SVM). In SVM, support objects are objects at the boundary of the class. The selection of support objects for the training set is different for different algorithms. The reason is that each algorithm has its own operating principle. For example, the objects considered as support for SVM are objects that are not informative for the partial precedence algorithm. Because the training set objects in the partial precedence algorithm are objects located in the center of the class and around the center.

At the same time, among metric algorithms, algorithms such as STOLP, λ-STOLP, FRiS-STOLP have emerged. STOLP means that it selects reference objects for metric classifiers. These types of algorithms are based on a greedy strategy, adding reference objects in a sequence. At each step of the algorithm, a benchmark is formed from the reference objects, that is, the benchmark is formed based on the local density of objects located in the maximum vicinity of the important object for the class. Objects located on the class boundary, as is known, serve as reference objects for the SVM algorithm.

The implementation of metric algorithms together with a somewhat improved mechanism for selecting reference objects is a very delicate and important situation. In this research work, a criterion for the effective use of the partial precedent method in implementing adaptive control and the concept of the compactness level of the training sample are proposed. The proposed algorithm is one of the algorithms of the STOLP class. First, this algorithm improves the functional performance by removing interfering objects from the sample. Then, less informative objects are removed from the sample. This process continues until the functional value becomes stable. At the end of the process, the objects in the training sample are divided into three categories: interfering, uninformative and reference objects. Adaptive control is characterized by training the partial precedent algorithm. Therefore, the algorithm that performs recognition using selected reference objects increases the classification quality somewhat.

Before solving the problem of pattern recognition, we introduce the following definitions. $(s_1, s_2, \dots, s_m) \in S$ is a set of objects, $(V_1, V_2, \dots, V_\ell) \in V$ is a set of values, and A is a set of algorithms. In most cases, A algorithms are also expressed in the form $A^*: S \longrightarrow V$. The reflection value $A^*(s)$ is equal to a finite set of objects $S_\ell = (s_1, s_2, \dots, s_\ell)$ and is called the training set or reference partial precedents. The response of the i-object in the training set is expressed by $V_i = A^*(s_i)$.

The algorithm for the learning problem $A^* \in \{A\}$ by precedent is built on three requirements. First, the training set must be given with predetermined answer values, that is, $A^*(s_i) = V_i$, $i = \overline{1, \ell}$. Here, equality should be understood as an approximation to a specific problem or an exact problem. This type of requirement is called locally bounded, that is, it is implemented with a finite number of training sets and an effective finite number of steps.

Second, the generality of the algorithm A^* introduces additional constraints, which require that the mapping of S to V be satisfied. For example, there may be constraints such as symmetry, continuity, smoothness, monotonicity. These constraints may also exist together. Constraints of this type are called universal requirements. They do not depend on a specific training set and depend on the complete mapping. As a rule, they do not allow for a finite number of effective checks, and this process is taken into account at the stages of developing the algorithm design. In general, universal constraints are expressed by the condition $A^* \in \{A\}$, where $\{A\}$ is a subset of algorithms, determined based on the nature of the problem.

Third, the algorithm A^* sought must have the ability to generalize, in which case it is possible to restore not only the dependence of V^* on the training set, but also to establish a dependence on all objects of the set S. This requirement can be formulated using various quality functionals.

The process of forming a training set is called training the algorithm being built. Its implementation is called recognition in the classification of a new object. As mentioned above, the objects in the training set are called reference partial precedents.

In the problem of pattern recognition in order to improve the efficiency of fire safety, the training sample will consist of $(i = \overline{1,m})$ objects s_i with a finite number of m for each class ℓ. If the training sample does not have any information about the level of activity, then the rules for dividing objects into classes based on their parameters are not specified. It also does not have a priori information about the probability of the existence of various classes and information about the recognition error. It is clear from this that a number of subjective proposals and specific hypotheses are needed to implement this or that algorithm in the problem of pattern recognition. At this stage, heuristic hypotheses are used to solve all real-world problems of pattern recognition.

The compactness hypothesis has long been known in the literature on pattern recognition and is used as an empirical hypothesis. In this case, objects of the same class are compact because they are located close to each other in the feature space from a geometric point of view, that is, densely. Despite its simplicity, this hypothesis is not only useful in pattern recognition, but also forms the basis of algorithms for intelligent data analysis. The compactness measure can be arbitrary: it is characterized by the distance between objects from the class center, is averaged close, or is a short-closed section, and provides a minimum distance within a class and a maximum distance between the centers of the classes.

Currently, there are various methods for improving the compact profile from the initial sample. These methods take two approaches to the problem: synthesizing the metric or the selected set of reference objects. In this work, the second approach was implemented. In this case, the training is aimed at isolating the reference objects from the sample, which is aimed at improving the quality of the algorithm recognition. When solving the problems of intelligent analysis of large amounts of data, it is necessary to develop new modified versions of the pattern recognition methods. To do this, the capabilities of the algorithm models are enriched by adjusting the parameters of existing algorithms or introducing new parameters.

A hybrid approach can be used to predict and optimally control the amount of methane gas, oxygen, temperature, and humidity in the air in high-fire risk facilities, where algorithms for calculation of estimates are used to classify based on current data. This approach can include the following steps:

1) Objective function and control parameters definition. Definition of an objective function that accounts for the risk of increasing methane concentration. This includes minimizing the probability of exceeding a critical concentration or maintaining the concentration within safe limits. In addition, control parameters may include: ventilation rate, ventilation frequency, degree of hermeticity, etc. [3]-[5].

2) Preparation of a model based on algorithms for calculation of estimates. Historical data on methane concentrations in the air are used to develop a model for algorithms for calculation of estimates. It classifies future concentration values into 3 classes (high fire risk, medium fire risk, no fire risk) based on current parameters such as gas, temperature, humidity and oxygen concentration. If the data includes measurements from multiple observation points, the algorithms for calculation of estimates can also take into account spatial distribution.

Compactness profiles are generated by metric classification algorithms. An example of this is partial precedence algorithms, where the profile shows how closely nearby objects fall into the same class.

Process 1:

1) Based on the profile principle that ensures the compactness of the training set $T_{nm\ell}$, the calculation is performed for each $S_i, i = \overline{1,m}$ object and $T_{nm\ell} \backslash S_i$ is removed from the training set.
2) Based on the principle of the selected recognition operator, a monotonic decreasing order is introduced between the fire $\delta(S_i)$ objects from the recognition stages.

Process 2:

Initial approximation.

- I_r= two nearby objects from different classes;
- $I_{\{s\}}$= all other objects;
- $I_s = \emptyset$; repeat repeat.

Optimize the solution of the problem with respect to λ_r:

$$\begin{cases}\frac{1}{2}\lambda_r^T\varphi_r\lambda_r + \varphi_{rc}\lambda_r - e_r^T\lambda_r \to \min_{\lambda_r}; \\ V_r^T\lambda_r + C_{e_C^T}{}_{\Gamma_c} = 0.\end{cases} \quad (1)$$

Algorithm for selecting base objects.

1) The distance of each object in the training set $T_{nm\ell}$ to the object $S_i, i = \overline{1,m}$ is calculated and sorted in ascending order.
2) Decommissioning of generating objects.

$$S = S',$$

repeat

$$S' = S'',$$

Process 1 is launched.

A new training set is formed from the objects that give the minimum value to the functional $\varphi(A^*, S_\ell) \to$ min:

$$S = \bigcap_{i:-\varepsilon\leq\delta(i)\leq 0} S_i'; \quad (2)$$

until $S' \neq \emptyset$.

3) Remove interfering objects on the edge of classes.

repeat $S' = S''$,

Process 1 is launched.

After removing distracting objects on the edges of the classrooms, a new learning path is formed:

$$S' = \bigcap_{i:-\varepsilon\leq\delta(i)\leq 0} S_i''; \quad (3)$$

until $S'' \neq \emptyset$.

4) The base object is inserted into the collection of objects as a result object S.

Classification algorithms based on the construction of a decision rule by identifying surfaces separating discriminant classes of discriminant profiles appear. In this case, the profile shows how the objects in the training sample are distributed in terms of distances relative to the dividing surface [6]-[8].

Input: $T_{nm\ell}$ training set.

C is a binary problem parameter.

Output: Linear classification parameters w, w_0.

1) Initial approximation.
2) I_v - two features objects of different classes;
3) I_m - all other objects;
4) I_c-$\emptyset$.
5) repeat.
6) repeat.
7) Solving the optimization problem with respect to λ_v:

$$\begin{cases}\frac{1}{2}\lambda_v^T T_{nm\ell}\lambda_v + C_{e_C^T} T_{nm\ell}\lambda_v - e_C^T\lambda_v \to \min_{\lambda_v}; \\ V_v^T\lambda_v + C_{e_C^T}V_c = 0.\end{cases} \quad (4)$$

8) If $|I_v|$>2 and $\exists i: i \in I_v \& \lambda_i \leq 0$ else $i \to I_v$;
9) If $|I_v|$>2 and $\exists i: i \in I_v \& \lambda_i \geq C$ else $i \to I_c$;
10) If there are $i \in I_v$ elements (objects), then continue until the remaining i elements fall into the subsets I_m or I_s.
11) Calculate the parameters of the algorithm w, w_0.
12) Let the constraints be calculated, $i \in I_m \cup I_c$.
13) If $|I_v|$>2 and $\exists i: i \in I_v \& m_i \leq 1$ else $i \to I_v$.
14) If $|I_v|$>2 and $\exists i: i \in I_v \& m \geq 1$ else $i \to I_v$.
15) While $i \in I_m \cup I_c$ do $\to I_v$.

The monotonicity profile gives rise to algorithms that satisfy the additional monotonicity constraint. Such algorithms are used as control operations, in particular, in the construction of algorithmic compositions. The profile shows how the order ratio density changes as the class boundary is approached [9]-[11].

1) Based on the profile principle, which ensures the compactness of the initial sample {S}, the calculation is performed for each object $S_i, i = \overline{1,m}$ and $\{S\}\backslash S_i$ is removed from the initial sample.
2) Based on the principle of the selected recognition operator, a monotonically decreasing order is introduced between the fire $\delta(S_i)$ objects from the recognition stages.

Algorithm for selecting base objects.

3) The distance of each object in the sample {S} to the object $S_i, i = \overline{1,m}$ is calculated, and the classification is performed by monotonic correction operations with $V = \{0,1\}$ and algorithmic composition: $A(s) = F\big(b_1(s), \ldots, b_T(s)\big)$, where $b_t \in B, t \in \overline{1,T}$, $b_t: s \to R$, $F: R^T \to \Gamma$. Here, V^T - is in monotonic increasing order.

A stability profile is generated for a wide class of methods that produce nearly identical algorithms with small changes in the composition of the training set. The profile shows how the algorithm's output is affected by the number of objects in the training set that change the quality of the results [12], [13].

The base object is included in the set of objects as the resulting object S. It was found that the following approaches can be used to improve optimal machine learning models to support fire safety decisions in fire hazardous facilities: data preparation and analysis, model selection and training, model optimization, model validation and verification, and iterative approach processes were studied. The constructive algorithms presented below include the above tasks of data preparation and analysis, model selection and training, model optimization, and model validation and verification.

Table 1: Input data for fire risk assessment.

№	Indicator name	Unit of measurement	Value	Note
1	Area of the object	m²	1200	Total area of the room
2	Amount of flammable materials	ton	15	Flammable materials present in the warehouse
3	Density of flammable materials	kg/m³	600	Storage density
4	Temperature	°C	28	Indoor ambient temperature
5	Humidity level	%	35	Humidity in the air
6	Number of electrical appliances	piece	50	Electrical equipment
7	Electrical network load	kW	120	Maximum load
8	Fire alarm system available	0/1 (yes/no)	1	1 – yes, 0 – yo‘q
9	Number of fire extinguishers	piece	8	Number of fire extinguishers
10	Number of employees	person	40	Number of employees at the facility
11	Number of evacuation exits	piece	3	Emergency exit doors

Table 2: Fire risk assessment results.

№	Indicator name	Weight (w)	Value (X)	Normalization (N)	Score (w×N)
1	Area of the object	0.10	1200 m²	0.60	0.06
2	Amount of flammable materials	0.20	15 t	0.75	0.15
3	Temperature	0.10	28 °C	0.50	0.05
4	Humidity level	0.05	35 %	0.40	0.02
5	Number of electrical appliances	0.10	50 piece	0.70	0.07
6	Electrical network load	0.15	120 kW	0.80	0.12
7	Fire alarm system available	0.05	1	0.10 (yes)	0.005
8	Number of fire extinguishers	0.10	8 piece	0.30	0.03
9	Number of employees	0.05	40 person	0.50	0.025
10	Number of evacuation exits	0.10	3 piece	0.20	0.02
	Overall score (Σ)				0.55

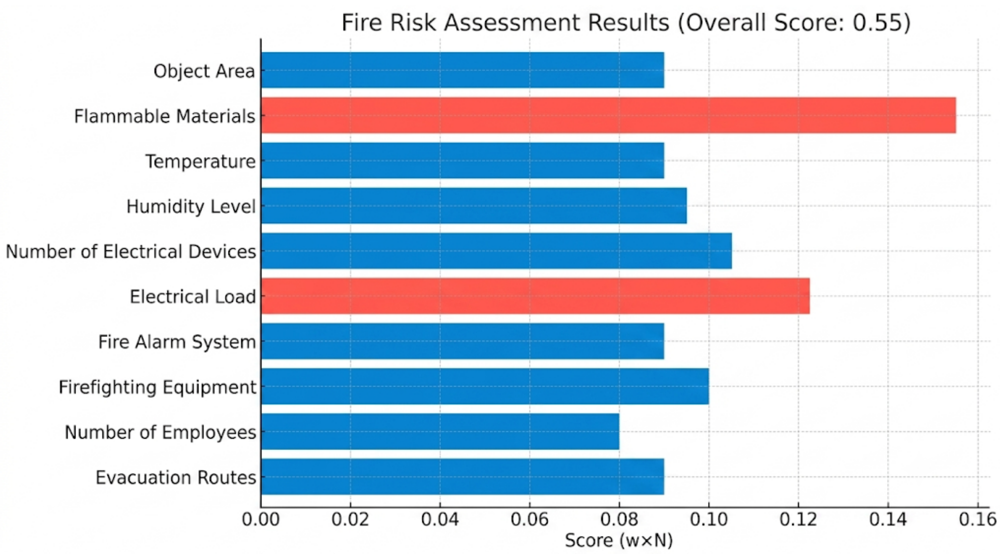

Figure 1: Graphical representation of fire risk assessment

Table 1 provides a summary of some of the key input data for fire risk assessment.

Table 2 shows the output table (i.e. the fire hazard level calculated by the assessment algorithm) based on the above input data. In this table, the overall integral assessment is calculated based on the weight of the indicators and the points:

Where:

- normalization (N) – evaluation of the indicator in the range [0…1] (based on standard or expert opinion);
- score (w × N) – contribution of each indicator to the overall risk;
- overall score (Σ) = 0.55 → this object belongs to the “Medium risk” category (0–0.4 – low, 0.41–0.7 – medium, > 0.7 – high risk).

The results of the fire risk assessment in tabular form were also presented in graphical form (Fig. 1).The graph shows the contribution of each indicator to the overall assessment - the red columns represent the factors with the greatest impact (combustible materials and electrical network load).

3 CONCLUSIONS

Ensuring safety at facilities with high fire risk is one of the most important issues for modern industrial and social infrastructure. Due to the limitations of traditional assessment methods, various problems arise in accurately predicting fire risk and making quick decisions. Therefore, the use of assessment algorithms is one of the most effective ways to solve this problem. The approaches considered in the study show that the use of mathematical models and algorithmic calculation systems to determine the level of fire risk at facilities allows for rapid, repeatable assessment of risk factors and their classification into categories, providing a foundation on which future real-time monitoring implementations could be built, as well as supporting the optimization of safety measures. This increases the effectiveness of fire prevention, protection of human life and property.

In conclusion, the approach based on scoring algorithms is of strategic importance in the field of fire safety, not only solving existing problems, but also creating the basis for further improving safety systems in the future.

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