Algorithms of a Digital Fire Prediction and Suppression System

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Abstract: This article analyses the algorithms of digital systems created to predict fire hazards and effectively eliminate them. Natural and man-made fires are one of the factors that cause great damage to human life, ecology and the economy. Fire risk prediction algorithms analyze environmental conditions such as weather patterns, wind speed, temperature, and humidity to assess potential fire hazards. These algorithms determine the level of risk in real time, predict possible fire situations and provide early warnings. In particular, the introduction of analytical models based on artificial intelligence significantly increases the accuracy of predictions. Fire suppression algorithms, on the other hand, allow for rapid coordination of actions after a fire is detected, optimal allocation of resources, automation of evacuation plans and effective management of emergency services. These algorithms embody complex solutions that include digital maps, real-time data exchange and inter-system integration. Therefore, the use of modern digital technologies and algorithmic approaches in ensuring fire safety is of urgent importance. This article examines the basic principles of fire prediction algorithms, namely, methods for predicting the level of risk based on factors such as weather data, air humidity, temperature, wind speed and plant dryness. It also analyses the mechanisms for determining the probability of a fire using artificial intelligence and machine learning models (for example, Random Forest, Neural networks). In addition, algorithms for quickly eliminating a fire after it is detected are considered, including optimal resource management, automation of evacuation plans, and the possibility of integrating drones and IoT devices into the system. To increase the efficiency of the system, algorithms based on real-time monitoring and digital maps are recommended. The results of the research work reveal the practical importance of advanced algorithms in firefighting and contribute to the development of digital approaches in the field of fire safety.

1 INTRODUCTION

Today, identification systems, monitoring of established fire risk thresholds using computer programs, and the development of a digital system are important issues. In developed countries of the world, in particular, Germany, France, Great Britain, Japan, South Korea, China, the Russian Federation and other countries, great attention is paid to solving theoretical and practical problems of intelligent analysis using artificial intelligence to assess fire safety at facilities with a high risk of fire and explosion, to develop measures to prevent precipitation.

The increasing material and moral damage caused by emergency situations occurring in the world every day, there is a need for scientific research on the development of traditional and modern methods of intellectual processing of information in digital systems, new approaches. In particular, great attention is paid to the theoretical and practical improvement of various models and methods of intellectual data analysis and Machine Learning. At the same time, understanding the mathematical foundations of Machine Learning models is important to assess their working principles, limitations, and advantages. Here are some of them. Decision trees are a model based on the principle of recursive partitioning, which can be subject to the problem of overfitting. Their advantages are that their interpretation is simple and understandable, and they do not require any predefined distribution. Random forests are an ensemble of a large number of decision trees, which can take a long time to train. Their advantages are that they work well with large amounts of data and can identify relationships between different attributes.

In this regard, scientific research is being conducted around the world to solve the problem of pattern recognition and create computational algorithms based on estimation algorithms. Among the important tasks is the development of a model algorithm and database, as well as a software package for preliminary processing of initial information based on regression analysis.

The effectiveness of fire risk management solutions is largely determined by the reliability and quality of data obtained from measuring instruments. Therefore, a separate task is to ensure the reliability of measurement data, identify incorrect (anomalous) measurements of controlled quantities, etc. This, in turn, allows you to increase the effectiveness of the fire safety system at facilities with high fire risk, as it determines the adequacy of management decisions taken to predict fire hazardous situations and prevent fires [1], [2].

2 METHODS AND RESULTS

Uncertainties in forecasting systems arise for various reasons, and as a result, the accuracy of the system may decrease. Optimized mathematical models are used to increase accuracy and improve decision-making processes. To minimize uncertainties in a forecasting system, the optimization problem is to maximize the accuracy of the forecasting system by reducing uncertainty. The accuracy and reliability of sensor data, computational resources and time constraints, the suitability and stability of model parameters, the suitability of the system for real-time operation, and the understandability of the forecasting results determine the limitations of the optimization problem.

The use of multi-stage analysis and an iterative approach method serves to gradually improve the results. Such an approach helps to increase the reliability of the forecasting system and ensure the efficiency of decision-making processes.

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To predict fire conditions, certain types of prediction methods were used in modeling processes based on data obtained from the device. Some of these prediction methods are listed below. Prediction methods: least squares method; extrapolation method of forecasting; sliding average method; exponential smoothing method; adaptive smoothing method; mathematical modeling method; network method; matrix method; simulation method, etc.

As part of the research work, an algorithm for predicting the occurrence of fire risks using a fire assessment model was developed (Figure 1).

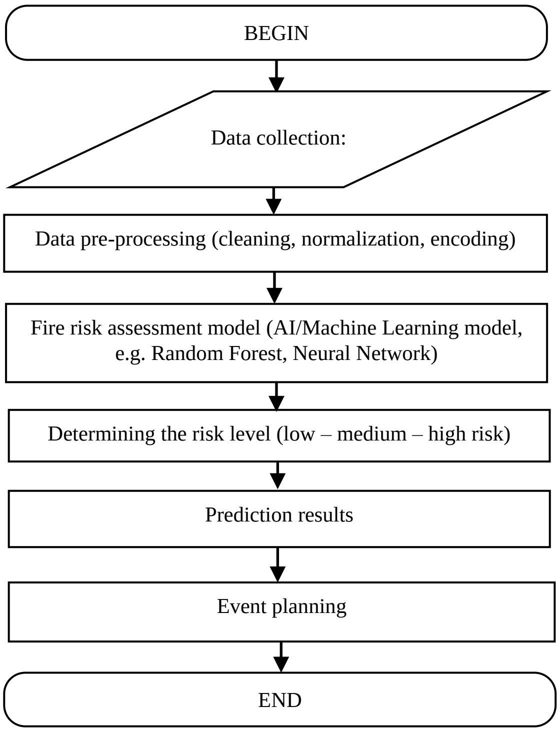

Figure 1: Block diagram of the fire risk prediction algorithm.

Data pre-processing (cleaning, normalization, encoding). The Kalman filter was applied to refine sensor data in real time, reducing noise and improving the reliability of fire risk assessment. The

Kalman filter is an efficient recursive filter that estimates the state vector of a dynamic system using a series of incomplete and noisy measurements. The Kalman filter is widely used in engineering and econometric applications, from radar and vision systems to estimating the parameters of macroeconomic models.

Fire safety systems constantly collect data and monitor the state in real time. Using the Kalman filter, this data is filtered and serves to prevent various interferences and ensure the effective operation of the predictive model.

A) Condition prediction (real-time analysis of sensor data). Using the state prediction formula in the Kalman filter, parameters such as temperature, gas concentration, oxygen, and humidity can be predicted:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k, \quad (1)$$

where:

1) $\hat{x}_{k|k-1}$ – predicted values of the parameters to be detected in the fire safety system (temperature, gas, oxygen and humidity);
2) F_k – a matrix describing the dynamics of changes in parameters (for example, temperature changes over time);
3) u_k – external influence (e.g. new information or external factors such as wind speed or air circulation).

The predicting process allows for early detection of fire risks and immediate action.

B) Covariance prediction (reducing data uncertainty).

Data from different sensors can always have a certain level of noise. The noise level of this data can be taken into account using the formula for predicting the covariance matrix:

$$P_{k|k-1} = F_k P_{k-1|k-1} + F_k^T + Q_k, \quad (2)$$

here, Q_k – system noise covariance. In fire safety, this noise can be caused, for example, by the sensitivity of sensors or by the external environment (dust, humidity, wind).

Thus, the filter helps to correct the data by taking this noise into account.

C) Kalman rule (data updating and correction). The Kalman rule can be used to correct data coming from a fire safety system:

$$K_k = P_{k|k-1} + H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1}, \quad (3)$$

here:

1) H_k – matrix of sensor measurements (for example, data from temperature, oxygen, gas, or humidity sensors);
2) R_k – measurement noise covariance. When the data is updated and there is noise or error in it, the Kalman rule is used to correct it. This increases the accuracy of fire risk detection.

D) Status update (real-time update of indicators). After the data correction process, the status will be updated:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}), \quad (4)$$

this formula can be used to adjust the prediction by taking into account the differences between the parameters determined in the fire safety system, for example, the temperature measured by sensors and the predicted value.

E) Covariance update. The covariance is updated after each updated data:

$$P_{k|k} = (i - K_k H_k) P_{k|k-1}, \quad (5)$$

there are 4 main types of forecasting: long-term, medium-term, short-term and operational (operational). In order to predict fire situations, certain types of forecasting methods were used to model processes based on data received from the device. Some of these forecasting methods are listed below. Forecasting methods: least squares method; extrapolation method of forecasting; sliding average method; exponential smoothing method; adaptive smoothing method; mathematical modeling method; network method; matrix method; imitation method, etc [3], [4].

The scheme of the optimal control process is basically the formulation of the optimal control problem as follows.

The problem of optimal management. The input parameters of the control system should be determined at such optimal values that the probability of fire occurrence is minimal and the accuracy of the information obtained from the object is increased.

Let us formalize the mathematical model of the problem. Let us consider a dynamic system described by the following equations of state.

$$x_{k+1} = f(x_k, u_k, w_k),$$

$$y_k = h(x_k, v_k),$$

here:

- x_k - is the state vector of the system at step *k*;
- u_k - vector of management effects;
- w_k - random effects of the process;
- y_k - measurable output parameters of the system;
- v_k - measurement noise (interference);
- $f(t)$ - system dynamics function;
- $h(t)$ - tracking function.

The optimal control problem is that the control effect should be chosen so that the following quality criterion has a minimum value:

$$I = \sum_{k=0}^{n} [Q(x_k) + R(u_k)], \qquad (6)$$

here:

- $Q(x_k)$ – penalty function for deviation of the state from the desired value;
- $R(u_k)$ – penalty function for management actions;
- n – prediction limit.

In the next step of the above block diagram, the first 5 values of the input data coming from the methane detection device are taken. Based on these values, the Kalman filter is calculated using the above model, and the input data of oxygen, humidity and temperature coming from the remaining 3 devices are also calculated [5].

Initial information (Table 1):

$$\hat{x}_0 = 0; p_0 = 1; A = 1; H = 1; Q = 0{,}01; R = 0{,}1.$$

Table 1: Input data.

Time	Tracking	Kalman filter
1	0	-
2	0	-
3	0,1	-
4	0,3	-
5	0,1	-

The results of these calculations are presented in Table 2.

Table 2: Calculation results.

Time	z_i - tracking	$\hat{x}_i$ - Kalman filter	P_i - covariance
1	0	0	0,0911
2	0	0	0,0503
3	0,1	0,0375	0,0375
4	0,3	0,1188	0,0321
5	0,1	0,0233	0,0296

By adding new adaptive coefficients to the Kalman filter, it is possible to further improve the efficiency of fire safety systems. The Adaptive Kalman Filter is mainly used. Adaptive coefficients and boundary coefficients help to quickly, accurately and flexibly determine the fire hazard. These introduced coefficients increase the real-time accuracy of the system and expand the ability to make quick management decisions in fire situations. To form a training sample model for analyzing sensor data interference using the Kalman filter, data from a methane sensor, which is considered the most important parameter in the occurrence of a fire, was separately extracted for one cycle sample. Using the Kalman filter, the input data graph, the data graph passed through the Kalman filter, and the improved Kalman filter graph were compared. Fire safety systems constantly collect data and monitor the situation in real time. Using the Kalman filter, this data is filtered, helping to prevent various interferences and ensure the efficient operation of the prediction model.

Uncertainties in forecasting systems arise for various reasons, and as a result, the accuracy of the system can decrease. Optimized mathematical models are used to increase accuracy and improve decision-making processes. To minimize uncertainties in a forecasting system, the optimization problem is to maximize the accuracy of the forecasting system by reducing uncertainty. The accuracy and reliability of sensor data, computational resources and time constraints, the suitability and stability of model parameters, the suitability of the system for real-time operation, and the understandability of the forecasting results determine the limitations of the optimization problem [6], [7].

The use of multi-stage analysis and an iterative approach method serves to gradually improve the results. Such an approach helps to increase the reliability of the forecasting system and ensure the efficiency of decision-making processes.

Table 3 shows the 4 parameters that are used to determine fire risk: Methane (CH_4) level, Oxygen (O_2) content, Humidity (%) and Temperature (°C).

Table 3: Input data by 4 parameters.

№	Methane level (ppm)	Oxygen level (%)	Humidity level (%)	Tempera-ture (°C)
1	1	20.8	65	28
2	8	21.5	35	34
3	3	21.0	60	25
4	6	20.1	40	32
5	4	20.9	55	26
6	10	21.9	30	36
7	5	20.5	48	29
8	9	21.8	38	33
9	…	…	…	…

Here:

- Methane level (ppm) - the amount of gas that increases the risk of fire (parts per million);
- Oxygen Level (%) – the percentage of O2 in the environment. A low level slows down combustion, a high-level speeds up the spread of fire;
- Humidity (%) – low humidity levels increase the risk of fire;
- Temperature (°C) – the higher the temperature, the more likely a fire will start [8], [9].

Table 4: Complete data table for the fire prediction system.

№	Methane level (ppm)	Oxygen level (%)	Humidity level (%)	Tempe-rature (°C)	Fire risk level
1	1	20.8	65	28	Low risk
2	8	21.5	35	34	High risk
3	3	21.0	60	25	Low risk
4	6	20.1	40	32	Medium risk
5	4	20.9	55	26	Low risk
6	10	21.9	30	36	High risk
7	5	20.5	48	29	Medium risk
8	9	21.8	38	33	High risk
9	…	…	…	…	

Risk assessment criteria (based on the logic of the model):

- High risk → Methane: 8-10 ppm, Humidity: 10-30%, Temperature: 30-60°C;
- Medium risk → Methane: 5–7 ppm, Humidity: 40–60%, Temperature: 22–29°C;
- Low risk → Methane: 1-4 ppm, Humidity: 70-90%, Temperature: 10-21°C.

The result table of accuracy and prediction using Decision Tree, Random Forest, K-Nearest Neighbors, and Artificial Neural Networks for the above data, Table 4 for a fire prediction system is Table 5.

Table 5: Comparison table by overall model Accuracy.

Algorithm name	Accuracy (%)
Proposed Algorithm	100 %
Decision Tree	100 %
Random Forest	100 %
K-Nearest Neighbors (K-NN)	87.5%
Artificial Neural Network	100 %

Among the tested models (Figure 2), Artificial Neural Networks (ANN) achieved the highest fire risk prediction accuracy (100%), outperforming traditional classifiers like Decision Trees (100%), Random Forest (100%), and K-Nearest Neighbors (87.5%).

In Figure 2:

- Decision Tree, Random Forest and ANN provide high Accuracy on this small dataset;
- K-NN can sometimes get confused with close classes (for example, it predicted Medium in the 2nd record);
- On the other hand, ANN and Random Forest are preferable on a large dataset because they are good at detecting complex relationships [10], [11].

Table 6 also presents an analysis of the results obtained using various machine learning methods in the study. The number of objects in the training sample was 7350, divided into 70% training and 30% control samples, and the number of input parameters was 4. The MSE (mean square error) function was used as the loss function.

Based on the positive results obtained above, the proposed model and algorithms are mainly used in objects with high fire risk (for example, gas stations, oil and gas processing plants, residential houses and other objects).

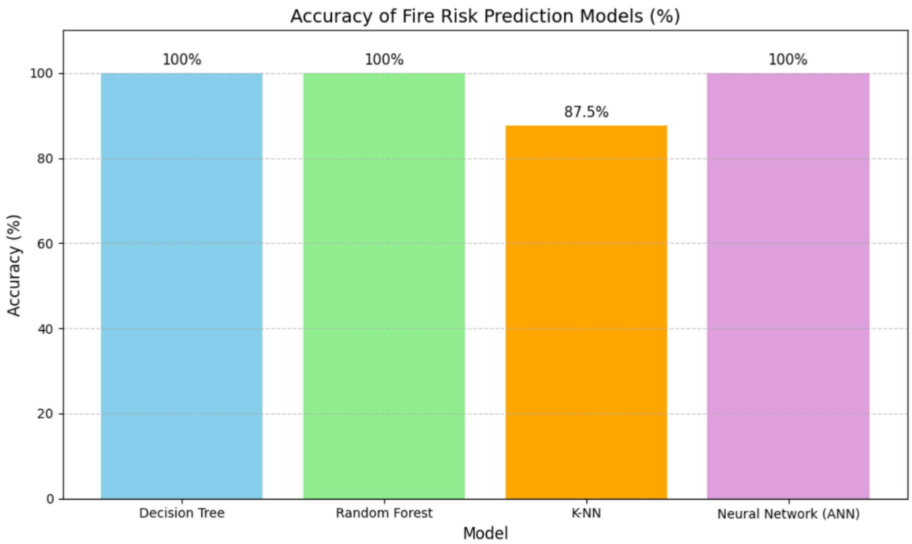

Figure 2: Accuracy of fire risk prediction models (%).

Table 6: Comparative analysis of Random Forest, kNN, MLP, Decision Tree and proposed algorithms.

№	Algorithm	Parametrs	Accuracy of training	Control accuracy (Accuracy)	Error values of the training sample	Error values of the control sample
1	Proposed Algorithm	Input Parameter: Improved Kalman Filter, Prediction Model	93.19%	92.01%	0.047	0.066
2	Random Forest	Trees: 10. Depth: None	82.18%	80.35%	0.208	0.133
3	kNN	Nearest Neighbors: 3. Distance: Euclid	81.02%	80.10%	0.279	0.211
4	Decision Tree	Core: RBF. C: 0.5. Gamma: 0.2	83.53%	81.45%	0.125	0.256
5	MLP	Hidden layers: (64. 32). Activation function: ReLU. Optimizer: Adam	92.10%	89.19%	0.024	0.014

3 CONCLUSIONS

The development of modern technologies creates the basis for the introduction of new approaches to ensuring fire safety. Digital systems aimed at predicting and extinguishing fires are intelligent platforms that allow for the early detection of natural and man-made fires, assessing the level of risk and taking effective measures. These systems operate based on AI, ML, sensor technologies and data analysis. Digital systems aimed at predicting and eliminating fires allow for early detection, monitoring, and rapid response to fire hazards based on modern technologies. These systems provide high accuracy in determining the likelihood of fires. This research proposed and validated a hybrid algorithmic framework that combines classical forecasting models with advanced tools such as the Kalman filter and adaptive ML models; including Random Forests and ANNs; which achieved up to 100% accuracy on specific datasets. The model's ability to process multi-parameter environmental data such as methane, oxygen, humidity, temperature and translate it into real-time risk levels demonstrates its practical applicability for high-risk environments such as fuel stations, industrial facilities, and residential areas. The inclusion of optimal control theory further enhances resource allocation and decision-making efficiency. Relative examination confirms the superiority of the proposed model in both prediction accuracy and computational performance when benchmarked against traditional classifiers. This paper not only highlights the value of hybrid predictive systems in mitigating fire hazards but also sets a foundation for future implementations involving IoT integration, drone deployment, and autonomous response mechanisms in dynamic environments.

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