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DEVELOPMENT OF AN ADAPTIVE METHOD FOR EARLY FIRE DETECTION BASED ON THE DYNAMICS OF CARBON FIRES IN THE GAS ENVIRONMENT FOR PREVENTION OF FIRE IN PREMISES

The object of research is the processes of formation and change of carbon monoxide concentration signals in the gas environment at the early stages of ignition of various combustible materials. The problem that was solved is to develop an adaptive method for detecting fires based on the use of current features of statistical instability of gas environment regimes preceding a fire. A method for early detection of fires by a carbon monoxide concentration signal is proposed, based on adaptive statistical processing using exponential smoothing and accumulation of instability energy. Unlike traditional approaches, the proposed method analyzes structural changes in the signal, which are manifested in an increase in variability and deviation from the current adaptive average. The method is implemented by forming a variational-squared indicator of fires, which is the product of the coefficient of variation and the deviation of the signal from its exponential average, squared, with subsequent exponential accumulation and normalization. It is shown that the obtained normalized statistics allow to maximize the probability of correct fire detection for a given false alarm probability. In the course of the research, expressions for the probabilistic characteristics of early detection were obtained and the problem of optimizing the exponential memory parameter was solved, which provides a compromise between sensitivity and noise resistance. Experimental validation showed that the proposed method provides earlier fire detection, a higher probability of detection at a given false alarm level and resistance to background signal drift. The practical significance of the method is determined by the possibility of its implementation in real-time early fire detection systems based on controllers with limited computing resources.

Keywords: *fire detection, carbon monoxide, coefficient of variation, exponential filtering, statistical detection, signal processing.*

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1. Introduction

Any fire (F) is an event with potentially catastrophic consequences, resulting in death and damage to human health [1], as well as to property and the environment. Such consequences are possible in the event of untimely localization of fires and their development into uncontrolled F. Developed fires lead to the collapse of building structures, which complicates further fire and rescue operations [2]. Fires at chemical and oil and gas industry facilities cause a cascading development of F, which leads to the almost complete destruction of such facilities [3]. Moreover, large-scale F lead to complex pollution of the atmosphere, soil and natural water sources [4]. F detection is traditionally based on the use of sensors sensitive to combustion products, such as smoke, heat and gaseous compounds, which always accompany the ignition and burning process. Since the release of gaseous compounds precedes the appearance of smoke and heat, gas sensors are considered a priority for the early fire detection (FD). To improve the FD efficiency, a transition to combined sensors for heat, CO, smoke and other combustion products is being developed [5].

Research in the field of early fire detection is based on recording physical and chemical signs of the initial stage of combustion, including aerosol particles, gaseous decomposition products and thermal effects [6], and has demonstrated the effectiveness of this approach. However, most researches focus on increasing the sensitivity of sensors rather than developing strict FD criteria [7]. Despite significant progress in the development of sensor technologies, the key problem is that at the early stage of a fire, a weak signal is generated, comparable in level to background fluctuations in the environment [8]. Therefore, the use of traditional detectors proves to be ineffective in solving early FD problems [9, 10]. Moreover, for example, smoke sensors are susceptible to false alarms caused by dust, water vapor or aerosols of non-flammable origin [10]. Thus, traditional detectors actually detect only developing fires, and not their early stages. Gaseous methods based on recording the concentrations of CO, CO_2 and O_2 are actively considered as a means of early FD [11]. This is explained by the fact that CO emission usually begins at earlier stages of material ignition compared to the appearance of smoke [8]. However, the use of CO is limited by the fact that it can arise as a result of processes unrelated to combustion [11], as well as by the individual dynamics of CO, which significantly depends on the type of material ignited and the current ventilation mode [8]. Therefore, no single gas parameter can be considered as a universal FD indicator. In this regard, multisensor systems combining different types of sensors are widely used to improve the FD reliability [7, 12]. However, analysis shows that most of these systems use simple threshold or empirical processing algorithms [7]. In this case, the stochastic nature of the signals and their temporal dynamics are not taken into account. In addition, a high correlation is observed between the readings of different sensors, which reduces the effectiveness of their combined use.

Computer vision and deep learning-based fire detection methods are actively developing [13]. They demonstrate high accuracy in detecting smoke and flame in visual data. However, these methods have a fundamental limitation: they are capable of detecting only already formed visual fire signs [13]. At the smoldering stage, when there are no visible manifestations, the effectiveness of such systems is significantly reduced. Additionally, the results are dependent on lighting conditions, smoke levels, and the quality of training samples. Modern research is aimed at integrating sensors with intelligent data processing algorithms and IoT infrastructure [12]. The use of machine learning methods makes it possible to take into account complex dependencies between environmental parameters. However, such systems remain largely empirical and require large volumes of training data. In addition, they do not provide physically interpretable criteria for early FD, which complicates the assessment of their reliability. In [14], it is proposed to implement early detection based on several sensors monitoring one of the hazardous parameters (HP) of the gas environment (GE) and subsequent network processing of the measurement information received from the sensors. This approach allows taking into account the statistical characteristics of the background of the observed HP, but the statistical features of the dynamics of the measurement information are not taken into account. A similar approach, but with the simultaneous observation of different types of GE HP, is considered in [15]. However, the developed approach also does not take into account the statistical features of the GE HP dynamics. Taking into account the statistics of the dynamics and the background based on the use of spectral features of the GE HP dynamics is considered in [16]. However, the use of spectral features significantly narrows the class of permissible GE HP dynamics, which significantly reduces the possibilities of early FD. The use of third-order spectra of the GE HP dynamics for early FD is studied in [17].

It is shown that third-order spectra allow to estimate the degree of correlation of frequency components in the spectrum, caused by the nonlinearity of the GE HP dynamics. It is noted that the degree of correlation of frequency components significantly depends on the energy of the measured HP. In addition, the practical use of third-order spectra turns out to be quite complex in implementation and is limited by the intervals of stationarity of the dynamics of the GE HP. The use of the average bicoherence of the GE HP dynamics as a sign of early FD is considered in [18]. However, the use of average bicoherence as a sign of early ignition is limited by the complexity of interpreting this sign and choosing an adequate criterion for the probability of FD and false alarm. In [19], methods for determining bicoherence based on a single realization and an ensemble of realizations of HP observations are studied. It is shown that determining bicoherence based on an ensemble of realizations turns out to be more preferable for early FD. However, the value of bicoherence in this case does not provide physically interpretable criteria for FD, which complicates the assessment of the quality of their detection. The use of the features of the empirical cumulative distribution function of the current recurrence of the GE HP dynamics as a feature of the early FD is considered in [20]. However, the application of this feature is limited by the complexity of the implementation of the computational procedure, which ultimately does not allow its use as a working feature of early FD. In [21], it is proposed to use the probability of the absence of recurrence of the increments of the state vector of the observed GE HP as a feature of early FD. However, the implementation of this feature is associated with complex calculations, which significantly limits its practical use for early FD. Moreover, this feature does not allow the formation of physically interpretable criteria for the FD quality, which generally complicates the assessment of the reliability of early FD. In [22], it is proposed to use the forecast of the GE HP increments for early FD. However, the researches are limited to considering the simplest Brown model, the parameters of which are determined by the a priori GE HP dynamics. Moreover, such a model belongs to the class of linear models. This significantly limits its application in real conditions. The use of the sample variance of the GE HP as a FD feature is considered in [23]. However, this feature is interval-based, which limits the operational FD effectiveness.

Thus, the problem of early FD remains fundamentally unsolved. Modern fire detection systems are generally focused on detecting a developing combustion process. However, the problem of identifying weak precursors of fire amidst ambient noise has no generally accepted solution. Furthermore, there is no unified mathematical criterion for early FD that would ensure the reliable detection of weak signals amid stochastic disturbances. This necessitates the development of methods based on the analysis of statistical signal characteristics, allowing for a transition from empirical threshold approaches to statistical detection criteria.

The object of this research is the dynamics of carbon monoxide concentrations in gaseous environments during the early stages of combustion of various combustible materials.

The subject of this research is methods and algorithms for processing CO signals aimed at identifying early signs of fire based on the statistical characteristics of the signal. *The aim of research* was to develop a method for early detection of material fires based on CO concentration dynamics that maximizes the probability of correct detection for a fixed false alarm probability through the use of adaptation principles and classical detection optimality criteria.

The objectives of research:

1. To validate a method for early fire detection based on CO concentration dynamics that maximizes the probability of correct fire detection for a given false alarm probability.
2. To validate the proposed method based on experimental data on the dynamics of CO gas concentration in a laboratory chamber during the ignition of typical combustible materials.

2. Materials and Methods

Any fire is accompanied not only by rapid ignition reactions, but also by relatively slow smoldering combustion reactions. Smoldering combustion releases a relatively small amount of thermal energy [24]. However, smoldering combustion is the decomposition of a material, leading to a significant release of various toxic gases and volatile compounds [5, 25]. Moreover, the released toxic gases and volatile substances pose a great danger to humans even before the appearance of thick smoke and open flame [26, 27]. In fact, inhalation of toxic combustion products is the main cause of death in fires [28, 29]. Moreover, detection of the moment when the concentration of toxic compounds exceeds the background level will allow for prompt and minimal cost elimination of the fire and prevent the occurrence of fire in the premise. According to [24], the process of release of toxic combustion products and heat is non-stationary. Therefore, early FD can be carried out based on the analysis of the statistical features of the non-stationary GE HP dynamics in the premise. At the initial stage of a fire, the level of emission of toxic reaction products and mechanisms of the combustion process of materials is usually insufficient for their rapid detection by threshold methods [30]. If the indoor GE is considered as a complex dynamic system with different modes, then a fire will cause a change in the current mode. Moreover, a change in the mode is characterized by non-stationarity, background drift and changing variance of the dynamics of the observed parameter of the indoor GE. This makes classical statistical methods of limited applicability, since the χ^2 and CUSUM methods require fixed distribution parameters, and the GLR method requires an explicit likelihood model. In real conditions, such assumptions are often violated. In this research, an alternative method is proposed, based on an exponential background estimate, the use of the variation coefficient as an indicator of instability and the energy accumulation of the square of the proposed adaptive indicator. The research materials for the verification of the proposed FD method were signals from a CO concentration sensor of the indoor GE in a laboratory chamber [31]. The chamber dimensions met the main criterion of similarity to simulate a typical unsealed room [32, 33]. The current CO concentration in the GE chamber was measured using a CO-B4 sensor (Alphasense, UK) [34]. The method was verified using the following test materials (TM): alcohol, paper, and wood chips. The ignition time for all TM was approximately 21–24 s relative to the start of the measurement. The CO sensor was sampled at a frequency of 10 Hz. The choice of TM was determined by different early ignition and CO generation reactions [35]. The measurement results for each TM were considered as a causal time series determined by a set $\{x(k)\}$ of CO concentration values at discrete moments in time k.

3. Results and Discussion

3.1. Substantiation a method for early fire detection based on CO concentration signals

The theoretical justification for the development of a method for early FD based on CO concentration signals is linked to three key technological clusters in the field of GE monitoring. In [36, 37], it is confirmed that exponential smoothing remains the "gold standard" for industrial monitoring due to its computational ease. However, in [38, 39], it is noted that classical filters with fixed parameters fail to cope with the non-stationarity of real CO emissions. Adaptive algorithms with changing smoothing coefficients during observations are preferable. However, in [38, 39], there is no reference to the energy indicators of the differences in the observed signals. At the same time, in [40, 41], the advantage of switching from amplitude analysis to signal energy analysis and the use of the chi-square distribution is substantiated. It is proven that for the early detection of gas emissions, quadratic forms of deviations are more effective in identifying process "disorders" than linear thresholds. However, in [42] it is emphasized that with an increase in background noise, the use of the Chi-square statistics leads to an increase in the probability of false alarms. At the same time, in [43, 44] it is shown that relative measures are the best detector of instability in dynamic systems, since they are invariant to the scale of the mean signal value. In this case, the variation coefficient is considered as an independent diagnostic feature, and not as a weighting factor for lag differences, which leaves the direction and speed of signal drift outside the scope of analysis. Another direction for the efficiency of CO monitoring is the improvement of the hardware [45, 46], taking into account that modern CO sensors are subject to temperature drift and aging. This makes it impossible to use the strict statistical models described in [47]. In [48, 49], solutions to this problem are considered based on the implementation of adaptive principles. Typically, the early stage of a fire is characterized by statistically significant small changes in the CO dynamics: an increase in the instability of the CO concentration dynamics is observed and the smoldering processes are non-stationary. This leads to an increase in the dispersion of CO dynamics even with a small change in its mean value [50]. Moreover, even a small, stable increase in CO concentration reflects the onset of thermal decomposition of the material [5]. Each of these features individually is an unreliable indicator of the onset of combustion, since high dispersion can be caused by the presence of external interference, and a small change in the mean can be masked by noise. However, their combined product allows to suppress random fluctuations (in the absence of an increase in the mean) and slow trends (in the absence of instability), and enhance non-stationary processes (characteristic of combustion itself).

Let's assume that the CO concentration $x(t)$ is described by a model of the form

$$x(t)=\mu(t)+s(t)+n(t), \quad (1)$$

where $\mu(t)$ – the slowly changing background component; $s(t)$ – the component due to early ignition; and $n(t)$ – the observation noise. Let's consider two hypotheses: hypothesis H_0: $s(t) = 0$ (no ignition), and hypothesis H_1: $s(t) > 0$ (there is ignition). Based on (1), it is necessary to choose one of the hypotheses. The solution must be optimal in terms of maximizing the probability of a correct decision for a given false alarm probability. Since the statistical and dynamic properties of signal (1) are unknown, it is proposed using current estimates of the mean and variance calculated using exponential filtering algorithms:

$$\mu_k=\left(1-\alpha_1\right)\mu_{k-1}+\alpha_1 x_k, \quad (2)$$

$$\sigma_k^2=\left(1-\alpha_2\right)\sigma_{k-1}^2+\alpha_2\left(x_k-\mu_k\right)^2, \quad (3)$$

where k – a discrete point in time $k = 0, 1, 2...$; $\alpha_1, \alpha_2 \ll 1$ – smoothing parameters. Based on (2) and (3), let's determine the current value of the variation coefficient

$$CV_k=\frac{\sigma_k}{\mu_k+\varepsilon}, \quad (4)$$

where ε – the division-by-zero protection. Value (4) characterizes the current instability of CO dynamics relative to the average.

Based on (2) and (4), it is possible to define statistics that account for the occurrence of an event (ignition) if both an increase in (4) and a current increase in the lag rate of CO concentration relative to estimate (2) occur. Such an event is typically characteristic of the physics of early material ignition. Therefore, for early ignition, let's represent the indicator as follows

$$I_k=CV_k\cdot\left(x_k-\mu_k\right). \quad (5)$$

Indicator (5) is essentially a modulated indicator of CO dynamics anomalies that is adaptive to background conditions, invariant to signal scales, sensitive to early stages of smoldering, and robust to observation noise and short-term spikes. The early FD method, based on the product of the current variation coefficient and the CO concentration deviation, provides increased sensitivity to non-stationary smoldering processes while simultaneously reducing the probability of false alarms. The method based on (5) takes into account both the statistical instability of the signal and its directional change, ensuring more reliable detection of the initial stage of fire under various background disturbances. To improve the robustness of the method based on (5) and generate sufficient statistics, it is proposed to switch to the accumulated energy of the indicator

$$S_k=\left(1-\alpha_3\right)S_{k-1}+\alpha_3 I_k^2, \quad (6)$$

where α_3 – the smoothing parameter for the indicator energy (5). Based on the resulting multiscale statistics (6), an estimate of the background energy is calculated

$$\mu S_k=\left(1-\beta\right)\mu S_{k-1}+\beta S_k, \quad (7)$$

where β – the smoothing parameter for the background energy (6). Using the proven approximation of the distribution tail of statistic (6) for small values of false alarm probability in the form of an exponential function, let's obtain an expression for the current FD threshold υ_k for a given false alarm probability value $P_{f\alpha}$

$$\upsilon_k = \mu S_k \left(-\ln\left(P_{f\alpha}\right)\right).$$

Then, the early FD rule based on statistic (6) will be defined as

$$S_k > \upsilon_k. \tag{8}$$

The probability Pd_k of a correct early FD for a given false alarm probability $P_{f\alpha}$ will be determined by

$$Pd_k > P_{f\alpha}^{\mu S_k / S_k}.$$

Statistic (6) is constructed using three exponential filters with different smoothing parameters α_1, α_2, α_3, taking into account the specific scales of the CO dynamics. Therefore, the choice of these parameters is not arbitrary. For consistency with statistic (6), it is necessary that $\alpha_1 > \alpha_2 > \alpha_3$. The background energy calculation should then be performed with the smoothing parameter $\alpha_1 > \alpha_2 > \alpha_3 >> \beta$. The specified smoothing parameters can be assigned to the characteristic time constants of the statistical features of the signals being studied ($\tau_1 < \tau_2 < \tau_3 < \tau_\beta$). Recalculation is performed using the formula $\alpha_i = 1 - e^{-\Delta t/t_i}$, where Δt – the signal sampling interval. For early FD, in accordance with the proposed method, the smoothing parameters and characteristic time constants of the statistical parameters of the non-stationary CO dynamics being studied are presented in Table 1.

Table 1

Smoothing parameters and characteristic time constants

Smoothing contour	τ, s	Characteristics
α_1	1–3	Average CO
α_2	3–10	CO variance CO
α_3	10–60	Energy
β	100–600	Background energy

It should be noted that the early FD rule (8) can be reduced to an equivalent rule of the form

$$R_k = S_k / \upsilon_k > 1. \tag{9}$$

Rule (9) is based on the statistic $R_k = S_k/\upsilon_k$ and the use of a fixed threshold equal to one for different fire conditions and materials. This is explained by the fact that the adaptive threshold is calculated taking into account the specified probability of a false alarm. Overall, the proposed method based on rule (8) or (9) implements a hierarchical system for assessing the non-stationary dynamics of a CO signal with division of time scales by levels of statistical information.

3.2. Validation results of the proposed early fire detection method

The method was validated using a single CO concentration realization for three types of HM (alcohol, paper, and wood shavings). For each HM, Fig. 1–3 show the corresponding time realizations of the change in the CO concentration (marked in green), statistics R (marked in blue), the probability of a correct FD P_d (marked in black), and the alarm signal (marked in red). In addition, in Fig. 1–3, the unit threshold for the corresponding statistics R is marked with a black dashed line. During the experiment, the exact time of ignition onset and the moment the system entered the steady-state mode were determined with finite uncertainty. Therefore, when assessing the FD characteristics, the analysis was carried out relative to the moment of a stable change in the CO concentration signal, and the transient process of adaptation to the background was not taken into account. When testing the method, the smoothing parameters were $\alpha_1 = 0.05$; $\alpha_2 = 0.01$; $\alpha_3 = 0.08$; $\beta = 0.008$.

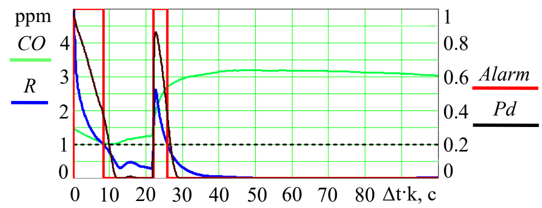

Fig. 1. Experimental dynamics of CO concentration, R statistics, correct detection probability, and alarm signal during alcohol ignition

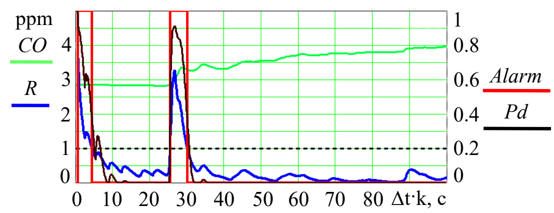

Fig. 2. Experimental dynamics of CO concentration, R statistics, correct detection probability, and alarm signal during paper ignition

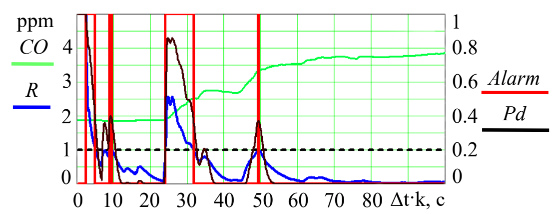

Fig. 3. Experimental dynamics of CO concentration, R statistics, correct detection probability, and alarm signal during wood shavings ignition

In all ignition scenarios, a consistent threshold exceedance and the generation of an *Alarm* signal were observed, based on the binary function $Alarm_k = II(R_k > 1)$. For various background conditions, threshold exceedances were short-term, random, and corresponded to the specified false alarm level.

3.3. Discussion

The fundamental feature of the proposed method is the use of a normalized indicator R, which is the ratio of the accumulated signal energy to the adaptive threshold level specified through the required false alarm probability $P_{f\alpha}$. In this formulation, the decision threshold is fixed and equal to $R = 1$, which eliminates the need for explicit threshold adjustment when observing conditions change. Fig. 1–3 demonstrate a picture in which $R < 1$ in the background mode, and its fluctuations are limited to a level corresponding to the specified $P_{f\alpha}$ level. Simultaneously, when TM is illuminated, there is a steady increase in the R statistics, followed by crossing level 1, and the moment $R \geq 1$ coincides with a sharp increase in P_d and the formation of the *Alarm* signal. This means that the R dynamics makes it possible to implement the statistical criterion of the maximum FD probability for a given false alarm probability. At the same time, alcohol (Fig. 1) is characterized by a rapid increase in the CO signal, which leads to a sharp increase in the accumulated energy and, as a consequence, to R quickly exceeding level 1. Crossing the unit level occurs almost immediately after the CO signal begins to change. The probability of the correct FD P_d quickly reaches values close to unity (0.86). The *Alarm* signal is generated with a minimum delay. This case demonstrates the operation of the method under conditions of a high signal-to-noise ratio. For paper (Fig. 2), a slower dynamics of CO growth is observed: energy accumulation occurs more slowly; the R statistics reaches level 1 with some delay.

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At the same time, the probability of the correct FD P_d increases and reaches a value of 0.9. The R statistics crosses the threshold level before the moment of a significant increase in CO, which confirms the sensitivity of the method to early changes in the dynamics of the signal statistics, and not only in its average level. The most complex case corresponds to the ignition of wood chips (Fig. 3): the CO concentration signal has less contrast and a higher noise level; the growth of the R statistics is cumulative; the R statistics reaches level 1 later compared to the ignition of other TM.

Nevertheless, even under these conditions, a stable FD is achieved, confirming the method's performance at a low signal-to-noise ratio. At the same time, it is here that the trade-off between the FD time and the $P_{f\alpha}$ level is most pronounced. The key advantage of the observed pattern is that the $R = 1$ level has a direct probabilistic interpretation (specified by the $P_{f\alpha}$ value). The behavior of the R statistic is comparable for different types of TMs, eliminating the need for empirical threshold selection. In fact, all differences between TMs are manifested not in the threshold level, but in the time it takes to reach the $R \geq 1$ condition. In the initial sections of the graphs, deviations in R are observed, sometimes leading to short-term intersections of level 1. This is due to the instability of the background parameter estimates used to form the threshold. After completion of adaptation, the condition of correspondence between the actual and specified false alarm probabilities is met, which is confirmed by the stabilization of the R behavior. Thus, the analysis of Fig. 1–3 demons trates that the proposed statistic R implements the normalized criterion for optimal detection with a fixed threshold of $R = 1$, ensures early FD through the accumulation of statistical deviations, and maintains a controlled false alarm rate, defined by the false alarm probability. Moreover, the proposed method demonstrates invariance to material type at the decision criterion level. The method's limitations are related to the initial adaptation stage, the increase in FD time for weak CO signals, and sensitivity to sudden, non-stationary disturbances. Unlike classical methods based on selecting a fixed threshold based on empirical selection, the proposed method determines the threshold in accordance with the specified false alarm probability, ensuring the early detection method's invariance to fire conditions and material types.

Practical significance: The obtained results can be used in practice as algorithms implemented on microcontrollers with limited computing resources (e. g., Arduino). The scope of the method is not limited to CO concentrations. The method and algorithms can also be used for other GE HP systems to prevent fires. Furthermore, the method can be used to detect malfunctions, failures, changes in instability modes, and anomalies in various non-stationary processes in the technical and natural spheres.

Prospects for further research: Since the method's validation was based on experimental data from CO tests involving materials ignited in a laboratory chamber, further research should be directed toward validating the method in fire tests under actual fire loads.

4. Conclusions

1. A method for early fire detection based on measuring CO concentration dynamics is substantiated. The method is based on a developed mathematical model of CO concentration signals, which takes into account the specific behavior of these signals under normal conditions and in the early stages of a fire. The model allows for the early detection of fires based on CO signals to be represented as a classical hypothesis testing problem. A standardization of the statistical detection indicator is proposed, in which the decision threshold is fixed at $R = 1$, and the threshold level itself is determined by a specified false alarm probability. It is shown that this approach provides a direct probabilistic interpretation of the early detection criterion and eliminates the need for empirical threshold adjustment. It is established that differences in observation conditions and types of combustible materials manifest themselves not in threshold changes, but in the time it takes to reach the condition $R \geq 1$, ensuring the invariance of the method. The proposed method ensures the maximum probability of correct fire detection based on CO concentration signals for a specified false alarm probability.

2. The method is validated using experimental implementations of CO concentration signals in a laboratory chamber during the combustion of alcohol, paper, and wood chips. It is experimentally confirmed that using the accumulated energy of deviations allows for early fire detection, before a significant increase in CO concentration. Validation on various types of combustible materials demonstrates that the developed method provides reliable early fire detection. It also guarantees the maximum detection probability (0.86–0.9) with a controlled false alarm rate (0.01), taking into account differences in CO signal dynamics and the signal-to-noise ratio.

Conflict of interest

The authors declare that they have no conflict of interest regarding this research, including financial, personal, authorship or other, that could influence the research and its results presented in this article.

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The research was conducted without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

Authors' contributions

Boris Pospelov: Methodology, Project administration; ***Evgeniy Rybka***: Software, Project administration; ***Viktor Pokaliuk***: Writing – review and editing; ***Larysa Maladyka***: Formal analysis; ***Oleg Bogatov***: Investigation; ***Svyatoslav Manzhura***: Supervision; ***Volodymyr Dachkovskyi***: Data curation; ***Marharyta Vorovka***: Writing – original draft; ***Svitlana Hryshko***: Conceptualization; ***Halyna Kalynychenko***: Resources.

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