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# Method for Detecting Fire Indoors Based on Differences in Sample Averages of an Arbitrary Gas Environment Dangerous Parameter at Adjacent Observation Intervals

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**Abstract.** The object of the research is the series average of the dangerous parameters of the gas environment during the ignition of materials. The practical importance consists of using the difference between the average dangerous parameters of the gas environment on the intervals of absence and the presence of ignition to detect the ignition of materials. The theoretical substantiation of the method of detecting fires in premises is carried out based on sample averages fixed samples of current measurements of an arbitrary, dangerous parameter of the gas environment, which correspond to the general population of reliable absence and presence of fire. At a given significance level, the method determines the unbiased, uniformly most powerful fire detection rule. This allows you to determine how significant differences in sample means with a given significance level are due to ignition or are random. Laboratory experiments were conducted to verify the method of detecting the ignition of test materials. It was established, for example, that the maximum size of the effect ignition on the carbon monoxide concentration is typical for alcohol (exceeds the threshold by 8.9 times) and textiles (exceeds the threshold by 9.3 times). The size of the effect of the smoke density upon ignition of all materials is approximately the same and is determined by exceeding the corresponding thresholds from 4.62 to 3.9 times. The size of the effect on the temperature of the gaseous environment during ignition of all test materials is approximately the same order. It is characterized by exceeding the corresponding thresholds from 5.95 to 3.58 times. It is shown that the method of detecting fires allows to establish the extent to which the detected differences in sample means for samples from the general population of hazardous parameters of the gas environment are reliable with a given level of significance and are due to the ignition of materials or the action of random factors.

## 1 Introduction

Recently, in most countries of the world, the total number of fires at facilities has been increasing [1]. The destructive effect of fires at facilities consists not only in the death of the civilian population [2] but also in the destruction and damage to the facilities themselves [3] and structural elements [4, 5]. In addition, the dangerous parameters of the fire itself, fire extinguishing agents, as well as technical means used to extinguish fires [6] affect the environment, causing pollution of water bodies [7], soil, and atmospheric air [8]. Statistics of fires in developed countries indicate that most occur in residential, public, and industrial facilities [9]. Moreover, over 50% of fires occur in residential buildings. Fires cause the greatest material damage to industrial (45%) and residential (35%) facilities. It is noted [9] that the maximum number of deaths from fire (80%) occurs in residential buildings. Moreover, fires in one- and two-family houses account for about 64.2% of deaths and 54.4% of injuries [10]. Fires in apartment buildings account for about 10.5% of deaths and 21.1% of injuries [11]. Following [9], the largest number of fires occur on premises for various purposes. In this regard, at the present stage in the problem of fire prevention, the implementation of various preventive measures, the use of fire detection methods, as well as fire prediction are considered priorities [12, 13]. At the same time, fire detection is extremely important for fire prevention. Fire detection methods allow you to quickly use modern automatic fire extinguishing systems and means and prevent fires, loss of life, and damage to equipment, structures, and objects. At the same time, fire detection methods are considered to be the most preferable compared to traditional fire detection methods since they make it possible to detect fires quickly and prevent a fire from occurring by extinguishing them promptly [14]. In this regard, at the present stage of development, fire detection (FD) methods should be considered as one of the pressing problems of ensuring fire safety on-premises. In English terminology, this problem is formulated as the problem of early fire detection.

In [15], the characteristic stages of fire are defined in the form of initiation (ignition), growth, full development and attenuation. At works [16, 17] note that the stages of fire and the maximum heat release rate significantly depend on the design features and fire loads of the premises. At the same time, it is noted in [18] that automation of fire safety in building premises has the highest priority. With the increasing complexity of the configuration of modern premises and the wide variety of fire loads, the sensitivity and accuracy of fire detection increases [19]. Traditionally used point sensors such as smoke, heat, and gas sensors have limited capabilities [20]. In this case, the stage of the fire must ensure that the hazardous parameters (HP) of the fire are reached from the source of the fire to the corresponding sensor and that the HP exceeds the established threshold value [21]. During this time, the fire can move from the ignition stage to the growth stage or even its full development [15]. In addition, the accuracy of fire detection is usually affected by various external disturbances, similar to HP, causing false alarms of sensors [22]. Thus, the main difficulty of early ignition using point sensors is their insufficient sensitivity and the individual complex dynamics of HP of the gaseous environment (GE) in rooms caused by the onset of ignition (I) of materials. At the same time, the mentioned works [15–22] do not consider FD methods based on the use of traditional fire sensors and improving methods of processing data from sensors, taking into account selected moments for the distributions of the current dynamics of fire alarms. In [23], for early detection of fires, it is proposed to use sensors for visual detection of smoke and fire. Detection methods are based on color analysis and machine learning algorithms. However, the complexity of a real fire and the presence of interfering influences significantly reduce the effectiveness of these methods [24]. In addition, the use of such sensors in the workplace reduces labor productivity and also violates the personal privacy of employees [25].

In [26], early fire detection in conditions of poor visibility and merging of the image with the background is proposed to be carried out based on infrared sensors. However, using image sensors in different wavebands and complex data processing techniques results in high detection costs. In addition, image sensors are prone to false fire detections if the ignition material is close to the sensor or if interfering influences exist [27]. To improve the quality of flame detection, a method based on using a neural network was proposed in [28]. A deep neural network learning method for early fire detection is discussed in [29]. However, despite the high performance, this method requires priori a large number of training data scenarios for various types of fires, as well as fire conditions, illumination, quantitative assessment of flame characteristics, and smoke intensity [23]. An experimental study of the combustion characteristics of three types of wood (two coniferous and one deciduous) at three levels of 30, 40, and 50 $kW \cdot m^{-2}$ heat source is presented in [30]. In this case, a linear relationship was established between the average rate of heat release during wood combustion and the intensity of the heat source, as well as the presence of two peaks in the heat release rate of samples from the beginning to the end of irradiation. In addition, the presence of two intense clouds of smoke was detected. One of them is before the wood ignites, and the other after it is charred. However, the dynamics of temperature and density of smoke during ignition and combustion of wood samples have not been studied. The features of the influence of the intensity of wood combustion on the temperature dynamics of the GE were studied in [31]. At the same time, the study's results are limited to the dependence of the average dynamics of the temperature of the GE on the average intensity of wood combustion. Similar studies for organic glass and cypress were carried out in [32]. However, in the works [30–32] there are no results of studying the features of the current dynamics and its selected moments for the dangerous parameters (DP) of the GE. For example, there are no studies of the features of sample average dynamics of the DP of GE during the intervals of absence and appearance of ignition. In [33], the current dynamics of DP of GE during the ignition of materials are studied. It is noted that the current dynamics of the DP of the GE during the ignition of materials is complex and nonlinear, which depends on the type of material and can be used as a sign for early detection I of GE. It is proposed to use the change in the amplitudes bispectrum of the DP. However, the methods for early detection of sensing based on the amplitude bispectrum of the DP are not considered in [33]. It should be noted that calculating the amplitudes of the bispectrum turns out to be difficult in practice due to several limitations. An FD method based on self-adjusting fire detectors with adaptive threshold settings is studied in [34]. This method makes it possible to detect I with guaranteed reliability. However, the research results are limited to adapting the threshold to the current power of the DP. In this case, the detection time of I largely depends on the value of the initial threshold. Other characteristics of the dynamics of the DP GE, for example, sample averages or sample moments of order higher than the second one, are not considered when adapting the threshold. The work [35] considers the method FD based on group data processing from many similar sensors using a neural network. The method of group processing of data from many different types of sensors is studied in [36]. However, the methods [35, 36] are limited to statistics no higher than second order, which do not allow the use of the nonlinearity features of the dynamics of the DP GE. In addition, these methods are complex and require specifying a library of reference dynamics of the DP in various I situations. Simpler methods for detecting I have not considered or studied. A method for assessing the reliability of detection of hazards in indoor environments is discussed in [37]. This method is based on the empirical cumulative distribution function of DP GE's current recurrence vector states. However, the recurrence of the state vector of the DP GE is a parametric procedure that is sensitive to the features of the specific dynamics of the DP states. In real conditions, the features of the DP dynamics are usually unknown and change over time. In [38], an adaptive method for determining the recurrence of the state vector of DP GE is considered. The method [38] is based on adapting the threshold when calculating the recurrence of the DP. Following [38], the threshold adaptation turns out to be only partial, allowing only the number of parameters to be reduced compared to [34]. At the same time, this method also turns out to be quite difficult to implement. At the same time, simpler methods, for example, based on selected moments of the dynamics of the state vector of the DP GE, are not considered in [38]. In [39], the FD method was proposed based on the time-frequency representation of fluctuations of the DP of the GE at the early stage of a fire in premises. However, this method remains quite difficult to implement. Simpler methods based on sample average values of the state vector of the DP GE are not considered in [39]. In [40], a method for correlating the current states of a complex dynamic system under conditions of irregular measurements is considered. In this case, the degree of correlation characterises the magnitude of the energy interaction of states, by the magnitude of which it is possible to quickly identify not only indoor pollution but also dangerous atmospheric air pollution. However, this method also turns out to be difficult to implement and is limited to consideration of the central second-order moment. Methods based on the first-order moment are not considered. The work [41] proposed a method for identifying atmospheric hazardous conditions based on the sample uncertainty function of the current vector of an arbitrary number and type of pollutants. It is proposed to determine the sample uncertainty function in a window of a fixed size moving along the dynamics trajectory (from 4 to 8 samples). It is noted that the method makes it possible to identify not only the moments of occurrence of dangerous conditions of atmospheric pollution but also to simultaneously determine their radial speed of movement relative to the control post. Despite the noted advantages of the method, determining the sample uncertainty function turns out to be quite difficult to implement, this limits its use for operational indoor inspection. Work [42] develops a method for detecting areas of hazardous atmospheric air pollution based on using the structure-function of the current recurrence of pollution concentration in a moving time window. The method allows us to identify the dynamics of the level and scale of local heterogeneities in polluted air. However, this method is complex. This limits its use for early detection of indoor fires. However, simpler methods are not considered. In [43], the spectral features of the dynamics of the DP GE during the ignition of materials are studied. It is noted that the amplitude spectrum is uninformative for FD. The nature of the random phase spread for frequency components above 0.2 Hz is informative for the phase spectrum. However, the results obtained are characterized by known limitations in using the Fourier transform. In addition, in [43], there are no DF methods based on the spectral features of the dynamics of the DP of the GE. Interestingly from the point of view of early FD are studies of the features of third-order spectra for the dynamics of the DP of the GE during fires. Studies of the average bicoherence of the dynamics of the DP of GE during the ignition of materials were carried out in [44]. It is noted that the identified features of the bicoherence dynamics of the DP GE averaged in the range from 0 Hz to 2 Hz can be used as a sign of the appearance of fires. However, FD methods based on average bicoherence are not considered. In addition, the determination of bicoherence in the case of non-stationary dynamics of the DP GE is associated with difficulties of a mathematical nature and is complex. The work [45] examines the features of the empirical cumulative distribution function of the recurrence of DP increments of the GE during the early combustion of materials. It is noted that the empirical cumulative distribution function of the recurrence of DP GE increments can be used as a sign of the occurrence of fires indoors. However, the combustion detection method based on the cumulative function is not considered. However, using this function to detect fires in real conditions is difficult. The use of the current measure of recurrence of DP of GE increments for operational fire forecasting is considered in [46]. It is shown that the current measure of the recurrence of DP GE increments is effective as a sign of early fires indoors. It has been experimentally established that the accuracy of fire prediction ranges from 4.48% to 12.79%. The possibility of using this GS feature in developing new early warning systems for indoor fires, as well as the modernisation of existing fire protection systems, is noted. However, the implementation of this feature in real time is limited by computational complexity. However, methods for simplifying the calculations of this characteristic are not considered.

Thus, from the analysis of literary sources, it follows that modern means and systems cannot carry out early detection of fire due to the materials in the room. It is proposed to replace traditional DP GE sensors with image sensors for early detection of indoor fire. However, this requires using complex image processing algorithms, which have certain limitations and capabilities. In addition, implementing early fire detection methods based on image sensors is an expensive solution to the problem. The use of traditional DP GE sensors with certain data processing methods makes it possible to solve the problem of detecting I materials on premises. However, known methods of processing data from traditional sensors using modern technologies turn out to be quite difficult to implement. Therefore, there is a need for simpler methods for detecting fire based on current measurements of the DP GE of the room. In this regard, an unresolved part of the problem of ensuring the fire safety of premises should be considered the development of simpler methods of FD based on current measurements of traditional fire sensors.

The purpose of the work is to develop a method for detecting fires in premises based on the use of differences in sample averages of an arbitrary dangerous parameter of the gaseous environment at fixed observation intervals. The fact that there are differences in sample average hazardous parameters of the gas environment at fixed observation intervals corresponding to the absence and presence of fires of materials can be used to detect fires to extinguish them and prevent a fire in the room promptly.

To achieve the goal of the work, the following tasks were set:

– perform a theoretical substantiation of the method for detecting fires in premises based on sample average current values of arbitrary dangerous parameters of the gaseous environment at two fixed observation time intervals;

– conduct laboratory experiments to test the proposed method for detecting fires based on dangerous parameters of the gas environment at intervals of the absence and presence of fires of test materials.

## 2 Main Part

The research materials were fixed-size samples from two general sets of measurements of the main DP GE, corresponding to the absence and presence of I of test materials (TM) in the laboratory chamber. The TM in the study were alcohol, paper, wood, and textiles. The measured parameters of the gas in the laboratory chamber were CO concentration, smoke density, and temperature GE. Temperature measurements were made with a TPT-4 sensor (Ukraine) [47], smoke density with an IPD-3.2 sensor (Ukraine) [48], and CO concentrations with a Discovery sensor (Switzerland) [49]. It was believed that the characteristic features of the influence of ignition of heavy metals on temperature, smoke density, and concentration of CO GE in a laboratory chamber are identical to the influence of these materials in real rooms [43]. At the same time, the size of the effect of the influence of I on the concentration of CO, smoke density, and temperature of the gas in the laboratory chamber for different TMs turns out to be different. This fact was considered when testing the proposed method for given types of TM.

## 3 Research Methods

The main research method was the sampling method. Data samples were taken from two general sets of DP GE measurements. The DP GE's first general set of measurements corresponded to the reliable absence of I material in the laboratory chamber. This general population was the training one. The second general set of DP GE measurements corresponded to the reliable presence of I material in the laboratory chamber. Measurements of DP GE [50], corresponding to the above general populations, were carried out by sensors located in the upper region of the laboratory chamber [51]. Measurements were performed discretely in time with an interval of 0.1 seconds. From the specified general sets of DP GE measurements, corresponding data samples of a fixed size, including 100 measurements, were extracted sequentially over time. The specified sample size ensured the representativeness of the corresponding general populations. Sample measurement data for each studied DP GE were stored in computer memory for subsequent processing - determining the corresponding sample averages and their errors. Based on the sample means and their errors for samples of DP GE from the corresponding general populations with a given level of significance, I was detected. In this case, the detection of I was carried out first for alcohol and then for paper, wood and textiles. After each I TM, natural ventilation of the laboratory chamber was carried out for 5–7 minutes. The need for natural ventilation of the laboratory chamber was intended to restore the initial state of the DP GE after I of each of the TM. The method for determining sample means and their errors was carried out in accordance with the methodology [52].

## 4 The Results of the Study

Any combustion of material in a room affects primarily the parameters of the GE. Among the parameters of the GE that are characteristic of the appearance of fires of various materials (at the early stage [53] of a fire) and are usually dangerous for humans, temperature, carbon monoxide concentration, smoke density, etc., as well as their derivatives are considered [54]. Therefore, these DP of the GE are traditionally used as signs of a fire in modern automatic fire alarm systems. However, these parameters can also be used for early detection of fires in order to prevent a fire from occurring [55].

Let us assume that there is a sample of a fixed size m of values of some arbitrary DP of the GE x1, x2,…, xm, where m=1, 2,…, m. The sample distribution function F(x) contains complete information about the properties of the sample [56]. At the same time, using F(x) in practice turns out to be quite difficult. Therefore, in applications, instead of F(x), they are often limited to considering its various selected moments [57]. The important and most frequently used of them are the first initial and second central sample moments, which characterise the position (means) and dispersion (variance or standard deviation) of distributions. In mathematical and statistical terms, the problem of early detection of fires can be formulated as follows. Let there be two general sets of values of an arbitrary DP of the GE, corresponding to the reliable absence and possible occurrence or absence of fire. In this case, the first set is training, and the second is being tested (absence or presence of sunburn). Let the sample extracted from the training population be characterized by the sample distribution function F1(x). And the sample extracted from the population being tested is characterized by the sampling distribution function F2(x). Then in the case absence of fire the condition is true F1(x) ≈ F2(x), and in the case of fire – F1(x) ≠ F2(x). Similar relations will be valid for the corresponding sample moments F1(x) and F2(x). This means that the FD method, in general, can be based on checking the homogeneity of various sample moments of the distributions F1(x) and F2(x). Let us consider first-order moments (sample means) as verifiable sample moments of the indicated distributions.

Let there be a sample of a fixed size m1 of values of some arbitrary DP of the GE x11, x12,…, x1m, where m=1, 2,…, m1 from the training population. Obtaining such a sample in practice is not particularly difficult since the corresponding training population corresponds to the normal conditions of an arbitrary DP of the GE in the room (no fire). To detect a fire, a second sample of a fixed size n2 of values of the same arbitrary DP of the GE x21, x22,…, x2n, where n=1, 2,…, n2 from the tested general population, is formed. Since the proposed method for early detection of fires is based on testing the homogeneity of sample means of sample distributions F1(x) and F2(x) in real-time, the training population must precede the population being tested. This means that, in accordance with the method under consideration, the sample x11, x12,…, x1m must precede in time the sample x21, x22,…, x2n. In this case, a decision on the presence or absence of fire is made for the time position of the sampling interval x21, x22,…, x2n. From the point of view of the efficiency of fire detection, it is advisable to reduce the sample size and consider them in time as adjacent samples. However, this way of increasing the efficiency of fire detection hides great difficulties of a mathematical nature [54-56]. To overcome these difficulties, it is proposed to use large sample sizes m1 and n2, which are over 50 values of an arbitrary DP of the DE. The first-order sample moment, in this case, has an asymptotically Gaussian distribution, the degree of approximation of which increases with increasing sample size. Moreover, as the sample size increases, the representativeness and accuracy of the first-order sample moment (sample mean) also increase [58].

Let us denote by X1 and X2 the sample means calculated from samples x11, x12,…, x1m and x21, x22,…, x2n, respectively:

$$X1 = \sum_{i=1}^{m1} x1i / m1, \tag{1}$$

$$X2 = \sum_{i=1}^{n2} x2i / n2. \tag{2}$$

Let's assume that X2 is different from X1. Does this mean that the true population means are different, or is this difference due to random reasons? In other words: what should be the difference X1 - X2 in order to consider it significant and assert that the true averages of the populations under consideration are really different and caused by the combustion of materials. The difference X1 – X2 can be studied using standard errors [58]. We believe that (1) and (2) are characterized by asymptotic Gaussian distributions $X1, s1/m1$ and $X2, s2/n2$ accordingly, in which $s1 = \sum_{i=1}^{m1} (x1i - X1)^2 / m1$ and $s2 = \sum_{i=1}^{n2} (x2i - X2)^2 / n2$ are determined by the accuracies (standard errors) of sample average values for samples x11, x12,…, x1m and x21, x22,…, x2n. Then the difference X1 – X2 will also have an asymptotically Gaussian distribution $X1 - X2, s1^2/m1 + s2^2/n2$, where $s1^2/m1 + s2^2/n2$ is the standard error for the difference $X1 - X2$. If we divide the difference X1 – X2 by $s1^2/m1 + s2^2/n2$, we obtain an asymptotic Gaussian distribution $X1 - X2, 1$ whose standard error equals one. In this case, to determine the probability of the difference $X1 - X2$ falling into an arbitrary interval, you can use the well-known table of the Laplace function [58, 59].

Thus, the FD method based on the difference $X1 - X2$ comes down to testing the null hypothesis (H0) that X1 – X2 = 0 against the competing hypothesis (H1) that $X1 - X2 \neq 0$. To test these hypotheses, a two-sided critical region is constructed based on the requirement that the probability of the normalized difference falling into this area, if the null hypothesis is true, is equal to the accepted significance level α (the probability of false detection of a fire). In this case, the greatest power of the FD method (the probability of the normalized difference falling into the critical region if the competing hypothesis is valid) is achieved in the case when the "left" and "right" critical points are chosen so that the probability of the normalized difference falling into each of the two intervals of the critical region, is equal to α/2. Given that the normalized difference in the case of the null hypothesis has a normalized Gaussian distribution $0,1$ that is symmetric about zero, the critical points will be symmetric about zero. This means that the probability of the normalized difference falling into the interval from 0 to ∞ is 0.5. This implies a method for determining the boundary of the two-sided critical region for the difference

X1 – X2 based on the argument of the Laplace function, which corresponds to the value of the function equal to (1-α)/2, and the standard error of the difference X1 – X2. Taking this into account, the FD method based on the difference X1 – X2 will be determined by inequality of the form:

$$|X1 - X2| > \Delta_{кр}, s1^2/m1 + s2^2/n2. \qquad (3)$$

where $\Delta_{кр}$ is the argument of the Laplace function, which corresponds to a function value equal to $(1-\alpha)/2$ . In this case, the area of acceptance of the null hypothesis (no fire) taking into account inequality (3) will be determined as:

$$|X1 - X2| < \Delta_{кр}, s1^2/m1 + s2^2/n2. \qquad (4)$$

Thus, the proposed FD method with a given probability of false detection (significance level α), defined by (3), provides the greatest power (probability of correct detection of fires). The fulfilment of the inverse inequality (4) indicates the absence of sunbathing and the validity of the null hypothesis. In this case, it is clear from the relations that to increase the ability of the method to detect small values of the difference |X1 – X2| the value of the right side of inequality (3) should be reduced. Given the significance of the method, this can be done by increasing the size of the corresponding samples. In the case of the same sample size for an arbitrary DP of the GE, the FD method (3) will take the following form:

$$|X1 - X2| > \Delta_{кр}, s1^2 + s2^2/p. \qquad (5)$$

In expression (5), the sample size $p$ should provide a Gaussian approximation of the distribution for the difference $X1 - X2$ . For large sample sizes, the proposed method is valid even when the values of an arbitrary DP of the GE have distributions that differ from Gaussian [60]. This is explained by the fact that the sample averages X1 and X2 are the sum of many terms, each of which has only a relatively small square deviation. Following [61], it can be shown that method (5) at a given significance level determines the uniformly unbiased most powerful FD rule. This means that rule (5) provides the maximum probability of detecting fires.

## 5 Experimental Verification of Fire Detection Method

As a result of a laboratory experiment, the proposed method for detecting fires was tested based on samples of measurement data of CO concentration, smoke density and temperature of the GE in a laboratory chamber during the fire of alcohol, paper, wood and textiles. The results of testing method (5) for the significance level α=0.05 when measuring CO concentration, smoke density and temperature GE are presented respectively in Tables 1–3.

**Table 1.** Results of testing method (5) for the concentration of carbon monoxide in GE at the significance level α=0.05

| № | param/mater | alcohol | paper | wood | textiles |
|---|---|---|---|---|---|
| 1 | \|X1–X2\| | 4.463 | 0.878 | 0.695 | 0.232 |
| 2 | $\Delta_{кр}$SE\|X1–X2\| | 0.499 | 0.247 | 0.145 | 0.025 |
| 3 | **rule (5)** | + | + | + | + |

**Table 2.** Results of testing method (5) for smoke density in GE at significance level α=0.05

| № | param/mater | alcohol | paper | wood | textiles |
|---|---|---|---|---|---|
| 1 | \|X1–X2\| | 0.241 | 0.188 | 0.043 | 0.086 |
| 2 | $\Delta_{кр}$SE\|X1–X2\| | 0.054 | 0.043 | 0.0093 | 0.022 |
| 3 | **rule (5)** | + | + | + | + |

**Table 3.** Results of testing method (5) for temperature in GE at significance level α=0.05

| № | param/mater | alcohol | paper | wood | textiles |
|---|---|---|---|---|---|
| 1 | $\|X1–X2\|$ | 3.549 | 1.374 | 0.376 | 0.563 |
| 2 | $\Delta_{кр}SE\|X1–X2\|$ | 0.596 | 0.295 | 0.105 | 0.157 |
| **3** | **rule (5)** | + | + | + | + |

In Table 1–3, the rows in which a positive rule to detect fires based on the proposed method (5) are marked with a plus sign are highlighted in yellow.

From the results presented in Tables 1–3, it follows that the proposed method with a significance level of α=0.05 generally makes it possible to detect fires for all TM on based samples of measurement data of CO concentration, smoke density and temperature GE in a laboratory chamber. Moreover, from Table 1 it follows that the detection I of alcohol by the concentration of CO GE is carried out at incise 8.9 times the threshold. Paper fire is detected at an incise 3.6 times the threshold. Wood combustion is detected when the threshold is exceeded by 4.8 times. Textile fire is detected when the threshold is exceeded by 9.3 times. Following Table 2, the detection of alcohol combustion based on measuring the density of the smoke GE is carried out when the threshold is exceeded by 4.46 times. In this case, paper fire is detected when the threshold is exceeded by 4.37 times. In this case, a wood fire is detected when the threshold is exceeded by 4.62 times. Detection of textile fire occurs when the threshold is exceeded by 3.9 times. For temperature, following Table 3, detection of alcohol combustion occurs when the threshold is exceeded by 5.95 times. The I of paper is detected when the threshold is exceeded by 4.65 times, and the I of wood and textiles is detected when the corresponding thresholds are exceeded by 3.58 times. From the analysis of the data in Tables 1 – 3, it follows that the combustion of all TM has a significant effect on the CO concentration, smoke density and temperature of the GE in the laboratory chamber. However, this influence is not the same for each material. For example, the maximum size of the effect on concentration CO is typical for the combustion of alcohol (exceeding the threshold by 8.9 times) and textiles (exceeding the threshold by 9.3 times). The size of the effect for the density of smoke when I all TM turns out to be smaller and approximately the same. In this case, it is determined by exceeding the corresponding thresholds from 4.62 to 3.9 times. The size of the effect on the temperature of the GE during the I of all TM also turns out to be approximately the same order of magnitude and is characterized by exceeding the corresponding thresholds from 5.95 to 3.58 times. It should be noted that the proposed FD method (5) allows us to determine how significant the identified differences in sample means for samples from the general populations under consideration are, that is, whether they are reliable with a given level of significance and are caused by I of materials or are the result of random factors.

Thus, the proposed method, taking into account a given level of significance, makes it possible to detect I of materials based on sample averages for fixed samples of measurements DP GE. The results were obtained do not contradict those known in the literature. The limitation of the study is associated with the choice of a given set of TM and DP GE in the laboratory chamber. The disadvantage of the study should be considered the impossibility of using the method in the current time for measuring the DP of the GE. Eliminating this drawback is associated with a corresponding modification of the proposed method. Further development of the study should be associated with overcoming the above limitations and disadvantages.

## 6 Conclusion

A theoretical substantiation of the method for detecting fires in premises has been carried out based on sample averages for fixed samples of current measurements of an arbitrary, dangerous parameter of the gaseous environment, corresponding to the general population of reliable absence and presence of fire. The proposed method, at a given significance level, determines the uniformly unbiased most powerful fire detection rule. The fire detection method makes it possible to determine to what extent the identified differences in sample means for samples from the general populations under consideration are significant, that is, whether they are reliable with a given level of significance and are caused by the fire of materials or are the result of random factors.

Laboratory experiments were carried out to test the proposed method for detecting fires based on the measured values of dangerous parameters of the gas environment at intervals of the absence and presence of fires of test materials. The test results showed that taking into account a given level of significance, the method makes it possible to detect fires of materials based on using sample averages for fixed samples of measurements of arbitrary dangerous parameters of the gas environment. It has been established, for example, that the maximum effect size on the CO concentration is typical for the combustion of alcohol (exceeding the threshold by 8.9 times) and textiles (exceeding the threshold by 9.3 times). The size of the effect on the density of smoke when igniting all TM turns out to be approximately the same and is determined by exceeding the corresponding thresholds from 4.62 to 3.9 times. The size of the effect on the temperature of the gas environment when igniting all materials turns out to be approximately the same order of magnitude and is characterized by exceeding the corresponding thresholds from 5.95 to 3.58 times. It is shown that the fire detection method makes it possible to determine to what extent the identified differences in sample means for samples from the considered general populations of dangerous parameters of the gas environment are significant, that is, whether they are reliable with a given level of significance and are caused by the fire of materials or are the result of random factors.

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