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DEVELOPMENT OF A METHOD FOR RAPID DETECTION OF FIRES BASED ON COMBINED CURRENT SAMPLING AND DISPERSIONS OF A CONTROLLED HAZARDOUS ENVIRONMENTAL PARAMETER

The object of research is the process of detecting the ignition of materials in a premise based on the joint use of current sample means and variances of the controlled hazardous gas environment parameter. The problem is to develop a method for detecting the ignition of materials based on the joint use of current sample means and variances of the controlled hazardous gas environment parameter in a premise. The synthesis of the optimal method for detecting fires was achieved by moving from the space of controlled hazardous gas environment parameters to the spaces of sample means, sample variances, and also the space of joint sample means and variances. Under conditions of large samples, the distribution of sample means, sample variances and its joint values asymptotically tends to a Gaussian distribution. This allows to use the likelihood ratio criterion, which is optimal, in the synthesis. Unlike the traditional approach, the likelihood ratio is current and is determined for a fixed Gaussian distribution in the case of a reliable absence of ignition. It is established that the optimal method of fire detection based on the joint use of sample means and variances with the same quality indicators outperforms the optimal methods of fire detection based only on the sample mean or sample variance of the controlled hazardous parameter of the gas environment. This is explained by the fact that the optimal method of fire detection based on the joint use of sample means and variances uses a larger amount of information contained in the controlled parameters of the gas environment. The results obtained are useful from a theoretical point of view for the proposed optimal methods of fire detection. The practical significance of the work lies in the further improvement of existing fire protection systems of facilities in order to prevent fires.

Keywords: *fire detection, premises, hazardous parameters of the gas environment, sample means, sample variance.*

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1. Introduction

The stability of any state is largely determined by the level of provision of safe operation of infrastructure facilities in the face of various threats. In peacetime and wartime, the greatest threats are fires at facilities. Fires are associated with human casualties, destruction and damage to facilities [1]. Fires at energy facilities are especially dangerous both in peacetime and wartime [2]. According to world statistics, in peacetime, most fires occur at residential, public and industrial facilities [3]. At the same time, the number of victims from fires in residential buildings is about 80 %. In this regard, the study of the problem of reducing the threat of fires in premises is relevant and has great practical importance. A constructive direction for reducing the threat of fires in premises is the ignition identification (II) of materials at the early stages of their occurrence. In [4], an approach to reducing the threat of fires in premises of facilities by II based on the use of video technologies is studied. It is shown that this approach generally allows reducing the threat of fire in premises. However, the II of materials based on video technologies is produced by the appearance of a flame. At the same time, the reduction of the fire threat in the premise in the absence of flame remains unresolved. The specified conditions are typical for the initial stage of a fire, when there is no flame during ignition (I) of materials. Studies in [5] show that the II efficiency based on the presence of flame in video images significantly depends on the shading of I materials and can decrease by 50–80 %. In addition, the presence of various distortions in images can increase the probability of false II to 0.2 or more. It should be noted that II video technologies require significant computing and intellectual resources. This significantly limits the capabilities of video technologies to reduce the fire threat in premises based on II in difficult conditions. A possible way to overcome the specified limitations of video technologies may be the II technology based on current monitoring of hazardous parameters (HP) of the gas environment (GE) during I of materials in real conditions. Such technology is studied in [6]. It is noted that GE HP in the premise carry complete information necessary for reliable and timely II of materials. However, it is not easy to obtain such information for the II, since this information is hidden in most cases, and also strictly individual for each type of premise and material I. This is explained by complex hidden mechanisms of interaction of the

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GE components with the beginning of the material I. In this regard, an important direction for reducing the risk of fire in a premise based on the current values of the GE HP should be considered the study of ways to identify and methods for using such information for the II in premises. In [6], the first and second order statistics of the GE HP are studied. However, these statistics contain complete information only in the case when the GE HP distributions correspond to the Gaussian law. At the same time, the study of real wood ignition is characterized by significant unevenness and complexity of the process of transferring the released heat to the environment. It is noted that this process differs significantly from the Gaussian process [7].

At the same time, the statistics of the heat transfer process and other GE HP at the stage of flame absence, which are important from the point of view of the II, are not studied. This increases the practical interest in the study of sample statistics of GE HP and methods of their use for the II at the initial stage before the appearance of flame. In [8], in order to identify hidden information contained in the GE HP, it is proposed to use several similar GE monitoring sensors and a neural network for data processing. However, it is known that the use of a neural network requires its preliminary training in specific conditions of materials. This significantly limits the II efficiency in real conditions, and also causes difficulties in determining the II quality indicators. The II capabilities based on monitoring sensors of various GE HPs with their subsequent processing by fuzzy logic methods are studied in [9]. However, the results of [8, 9] are limited to considering only the first and second order statistics of the monitored GE HP. In addition, the disadvantage of the approach [9] is the complexity of implementing fuzzy logic methods and algorithms that require a large amount of a priori information, which is usually unknown and can change during the GE HP inspection. In this case, other statistics of the GE HP are not considered. It should be noted that all the results considered above relate to the time domain of inspection of the GE HP and II. However, the time domain can be matched with an equivalent frequency domain of II. The study of the GE HP features at intervals of absence and presence of I of materials in the frequency domain is considered in [10]. It was found that the differences in the spectra with I of materials are more characteristic of the high-frequency components of the monitored GE HP. At the same time, there are no connections between the frequency components in the spectra, which makes them insensitive to the nonlinearity of the change in the GE HP, which is usually inherent in the initial stage of I of materials. This limits the application of the spectra for II. In [11], the differences in the bispectra of the GE HP at the stage of I of materials are studied. It is shown that, unlike traditional spectra, bispectra are sensitive to the features of the HP nonlinear dynamics. The study of the GE HP bicoherence on the intervals of reliable absence and appearance of I of materials is devoted to the work [12]. It is shown that there are differences in bispectra that can be used for II. However, it is difficult to calculate the II quality indicators based on spectra and bispectra. In addition, in practice, the control of the GE HP is carried out in the time domain. Therefore, when using the features of spectra and bispectra for II, there is a limitation associated with the correctness and accuracy of the transition from the time to the frequency domain in the case of non-stationarity, uncertainty and nonlinear nature of real GE HP.

Thus, the solution to the problem of reducing the risk of fires in premises is closely related to ensuring II early detection of materials. Two main approaches are used for this. The first approach is based on obtaining a video image of the controlled I area and applying image processing algorithms using complex methods of machine learning and pattern recognition. The implementation of this approach involves the use of expensive video image sensors, a large base of reference images of I of materials, servers for its storage, as well as the presence of reliable information exchange channels. In general, this leads to a loss of efficiency, reliability and autonomy of the II process in real premises. The second approach is based on the development and application of methods for statistical processing of controlled GE HP using traditional fire sensors. However, the development of this approach is hampered by insufficient research into the features of various distribution statistics controlled by GE HP. Firstly, this is due to a wide variety of premises, as well as conditions and types of I of materials. Secondly, it is explained by the secrecy and sufficient complexity of the mechanisms of interaction of the emitted products with the controlled GE HP at the initial stage of fire development in the premises. The features of joint distributions of current sample means and variances of controlled GE HP for II in real time remain insufficiently studied.

The aim of research is to develop a method for detecting material fires based on the joint use of current sample means and variances of the controlled hazardous parameter of the gas environment in the premise and to perform its experimental verification during the ignition of test materials in a laboratory chamber. The use of the method will allow for the timely detection of material fires in order to extinguish them and reduce the risk of fire with losses in various premises.

2. Materials and Methods

The object of research is to detect fires of materials in a premise based on the combined use of current sample averages and variances of the controlled hazardous parameter of the gas environment. The study was conducted under the assumption that a fire of a material in a premise leads to a change in both the physical parameters of the material itself and the GE parameters. Usually, a fire of a material is accompanied by a transfer of excess enthalpy to the ceiling area of the premise, leading to an increase in temperature and turbulence of the GE in the ceiling area [13]. This means that it is possible to carry out II based on the features of statistical distributions of the GE HP before and upon occurrence of a fire of materials. However, it is not possible to theoretically identify the specified features of the GE HP distributions. Therefore, the study was conducted experimentally. For this purpose, a laboratory chamber was created simulating a non-hermetic premise. The dimensions of the chamber were: 1500×1000×500 mm. In the upper area of the chamber, above the source of fire of the material, sensors were placed to monitor temperature, optical density of smoke and concentration of carbon monoxide [14]. This arrangement of the sensors for monitoring the specified GE HP in the chamber made it possible to study the features of their statistical distributions with a real I of materials [15]. It is the II methods based on the differences in the statistical distributions of the GE HP with a I of materials in the premises that are important in the practice of reducing the risk of fire. During the study, the GE temperature in the chamber was monitored using a DS18B20 sensor (USA), the specific optical density of smoke was monitored using an IPD-3.2 sensor (Ukraine), and the CO concentration was monitored using a Discovery sensor (Switzerland) [16]. The study materials were the results of monitoring the output signals of the specified sensors in the absence and presence of I of test materials (TM). Alcohol, paper, wood, and textiles, characterized by different specific mass burnout rates of materials, were selected as TM [17]. Monitoring of the values of the output signals of the sensors studied by the GE HP as performed discretely in time with an interval of 0.1 seconds. The obtained discrete values of the output signals of the sensors were saved in the computer memory for subsequent processing. For an arbitrary monitored GE HP, the values of the output signals of the sensors were a set of sequential data in time x_0, x_1, x_2, ..., x_M, where M determines the end time of a given monitoring interval (research interval) [18]. For an arbitrary sample of size N ($N<M$) from data x_0, x_1, x_2,..., x_M, the statistical distributions are usually unknown and differ from Gauss. However, if the sample size N satisfies the large sample condition (e. g., over 60), then the statistical distributions of the sample means and variances asymptotically approach Gaussian with the corresponding parameters [19]. Taking into account the independence

of the sample means and variances for the Gaussian distribution, their joint distribution will also be asymptotically Gaussian. This allows to determine the quantitative indicators of the II quality in the space of sample means and variances of the monitored GE HP. In addition, in such a space, it is possible to formulate and solve problems of finding the optimal II method based on the likelihood ratio rule. Let's consider the essence of the optimal II method in the space of sample means and variances in discrete control of the GE HP. It is possible to assume that the first N data from the set $x_0, x_1, x_2, ..., x_M$ $(N<M)$ correspond to a sample from a certain general population, characterized by the I absence, the I appearance or presence. If N satisfies the condition of a large sample [18, 19], then the sample mean and sample variance will be determined:

$$\alpha_N=\sum_{i=0}^{N-1}x_{N-i}/N, \beta_N=\sum_{i=0}^{N-1}(x_{N-i}-\alpha_N)^2/N. \quad (1)$$

In this case, the variances for the sample mean and sample variance (1) will be determined by the values:

$$D_{\alpha N}=\beta_N/N, D_{\beta N}=\left(\sum_{i=0}^{N-1}(x_{N-i}-\alpha_N)^4-\beta_N^2\right)/N. \quad (2)$$

Relations (1) and (2) determine the maximum likelihood estimates for the moments of the corresponding distributions, which are asymptotically Gaussian. This means that in the space of arbitrary sample means α and variances β, their joint distribution will be determined by:

$$p_N(\alpha,\beta)=p_N(\alpha)p_N(\beta)= =\exp\left\{\begin{matrix}-(\alpha-\alpha_N)^2/2D_{\alpha N}- \\ -(\beta-\beta_N)^2/2D_{\beta N}\end{matrix}\right\}/2\pi D_{\alpha N}D_{\beta N}. \quad (3)$$

Taking into account representation (3), the joint distribution for arbitrary sample means α and variances β in the case of a sample of size N, shifted at time $j=1, 2, ..., M$, i. e. at time $N+j$, will be determined as:

$$p_{N+j}(\alpha,\beta)=\exp\left\{\begin{matrix}-(\alpha-\alpha_{N+j})^2/2D_{\alpha N+j}- \\ -(\beta-\beta_{N+j})^2/2D_{\beta N+j}\end{matrix}\right\}/2\pi D_{\alpha N+j}D_{\beta N+j}. \quad (4)$$

Based on (3) and (4), the transition likelihood ratio $l_j(\alpha, \beta)$ at an arbitrary time j relative to time N will take the form:

$$l_j(\alpha,\beta)=p_{N+j}(\alpha,\beta)/p_N(\alpha,\beta)=l_j(\alpha)l_j(\beta), \quad (5)$$

where $l_j(\alpha)=p_{N+j}(\alpha)/p_N(\alpha)$ and $l_j(\beta)=p_{N+j}(\beta)/p_N(\beta)$ are the corresponding partial transition likelihood ratios. Taking into account representation (5), the optimal II rule at time j in the space of arbitrary sample means and variances will be determined as:

$$l_j(\alpha,\beta)=l_j(\alpha)l_j(\beta)\leq 1, \quad (6)$$

$$l_j(\alpha,\beta)=l_j(\alpha)l_j(\beta)>1. \quad (7)$$

Inequality (6) defines the optimal decision rule about the I absence at time j (hypothesis H_0), and inequality (7) defines the optimal decision rule about the I presence at time j (hypothesis H_1). Since the partial transition likelihood ratios in the space of sample means and variances are analytically defined and are Gaussian, it is possible to determine quantitative indicators of the quality of solutions (6) and (7). Let's consider the essence of the partial transition likelihood ratio $l_j(\alpha)$ in more detail. Taking into account (3) and (4), the partial transition likelihood ratio $l_j(\alpha)$ can be represented as:

$$l_j(\alpha)=\exp\left\{\begin{matrix}(\alpha-\alpha_N)^2/2D_{\alpha N}- \\ -(\alpha-\alpha_{N+j})^2/2D_{\beta N+j}\end{matrix}\right\}\sqrt{\frac{D_{\alpha N}}{D_{\alpha N+j}}}. \quad (8)$$

It follows from (8) that $l_j(\alpha)$ at time j depends on three parameters α, α_N, α_{N+j}, two of which are the maximum likelihood estimates of the sample mean for samples of size N at times N and $N+j$. In this case, the maximum (8) will take place at $\alpha=\alpha_N$. This means that for the maximum likelihood estimate of α_N at time N for a sample from the general population corresponding to the reliable absence of Z, representation (8) will take the form:

$$l_j(\alpha_N)=\exp\left\{\frac{-(\alpha_N-\alpha_{N+j})^2}{2(D_{\alpha N+j}+D_{\alpha N})}\right\}\sqrt{\frac{D_{\alpha N}}{D_{\alpha N+j}+D_{\alpha N}}}. \quad (9)$$

Taking the logarithm and transforming (9), the II optimal rule at an arbitrary time j based on the partial transition likelihood ratio of the sample mean will be determined as:

$$(\alpha_{N+j}-\alpha_N)\underset{H_1}{\overset{H_0}{\lesseqgtr}}\sqrt{\ln\left(1+\frac{D_{\alpha N+j}}{D_{\alpha N}}\right)}\sqrt{D_{\alpha N+j}+D_{\alpha N}}. \quad (10)$$

In this case, if the condition $H_0/\leq$ is met, then a decision is made about the I absence, if $>/H_1$ – decisions about the I presence. Since the sample α_N, α_{N+j} in (10) have asymptotically Gaussian distributions, their difference is also asymptotically Gaussian. In this case, the value $(\alpha_{N+j}-\alpha_N)/\sqrt{D_{\alpha N+j}+D_{\alpha N}}$ has an asymptotically Gaussian distribution with unit variance. This means that if the estimates α_N, α_{N+j} are determined for samples from similar populations corresponding to the reliable absence of I, then their normalized difference will have an asymptotic Gaussian distribution with a mean close to zero and unit variance. In this case, using the Laplace integral, it is possible to determine the value of the threshold $\Delta\gamma$ corresponding to a given significance level γ (reliability) of the solution. Taking this into account, the rule of optimal II (10) with a given significance level γ (reliability) will be determined:

$$(\alpha_{N+j}-\alpha_N)\underset{H_1}{\overset{H_0}{\lesseqgtr}}\Delta\gamma\sqrt{D_{\alpha N+j}+D_{\alpha N}}\sqrt{\ln\left(1+\frac{D_{\alpha N+j}}{D_{\alpha N}}\right)}. \quad (11)$$

The optimal rule (11) differs from the known rules obtained on different assumptions without using the likelihood ratio by an additional correction of the known threshold $\Delta\gamma\sqrt{D_{\alpha N+j}+D_{\alpha N}}$ by multiplying it by the value $\sqrt{\ln(1+D_{\alpha N+j}/D_{\alpha N})}$. Carrying out similar transformations for the particular transition likelihood ratio $l_j(\beta_N)$, it can be shown that the optimal II rule with the same significance level γ will be determined by:

$$(\beta_{N+j}-\beta_N)\underset{H_1}{\overset{H_0}{\lesseqgtr}}\Delta\gamma\sqrt{D_{\beta N+j}+D_{\beta N}}\sqrt{\ln\left(1+\frac{D_{\beta N+j}}{D_{\beta N}}\right)}. \quad (12)$$

Taking into account (6) and (7), as well as (11) and (12), the optimal II rule with a given significance level γ in the space of joint sample means and variances will be determined by:

$$(\alpha_{N+j}-\alpha_N)(\beta_{N+j}-\beta_N)\underset{H_1}{\overset{H_0}{\lesseqgtr}}\Delta\gamma^2 S_{N,j}, \quad (13)$$

where $S_{N,j}=\sqrt{(D_{\alpha N+j}+D_{\alpha N})(D_{\beta N+j}+D_{\beta N})\ln\left(1+\frac{D_{\alpha N+j}}{D_{\alpha N}}\right)\ln\left(1+\frac{D_{\beta N+j}}{D_{\beta N}}\right)}$ is the generalized error for the product of differences between the current sample means and sample variances at an arbitrary time j.

Rule (13) determines the optimal II method at an arbitrary time j with a significance level γ, which is based on the transition likelihood ratio (5) in the space of joint sample means and variances. The proposed

II method was subject to verification based on experimental data obtained during the TM ignition in a laboratory chamber.

3. Results and Discussion

Based on relations (11)–(13), it is possible to write the final formulas that determine the optimal II methods based on the use of sample means, sample variances, and their combined use as follows:

$$Amo_p=(\alpha_{N+p}-\alpha_N)-\Delta\gamma\sqrt{D_{\alpha N+p}+D_{\alpha N}}\sqrt{\ln\left(1+\frac{D_{\alpha N+p}}{D_{\alpha N}}\right)}\underset{H_1}{\overset{H_0}{\underset{>}{\leq}}}0, \quad (14)$$

$$Bdis_p=(\beta_{N+p}-\beta_N)-\Delta\gamma\sqrt{D_{\beta N+p}+D_{\beta N}}\sqrt{\ln\left(1+\frac{D_{\beta N+p}}{D_{\beta N}}\right)}\underset{H_1}{\overset{H_0}{\underset{>}{\leq}}}0, \quad (15)$$

$$AB_p=(\alpha_{N+p}-\alpha_N)(\beta_{N+p}-\beta_N)-\Delta\gamma^2 S_{N,p}\underset{H_1}{\overset{H_0}{\underset{>}{\leq}}}0, \quad (16)$$

where $p=0, 1, 2, ..., 2000$.

Formulas (14)–(16) allow to compare the indicated optimal II methods since they have the same right-hand sides. The results of the experimental comparison of such optimal II methods for four TMs of ignition in a laboratory chamber at the same significance level $\gamma=0.05$ and fixed $N=100$ for the concentration of carbon monoxide are shown in Fig. 1.

In this case, the content of the designations along the ordinate axis in Fig. 1–3 corresponds to the right-hand sides of expressions (14)–(16), respectively.

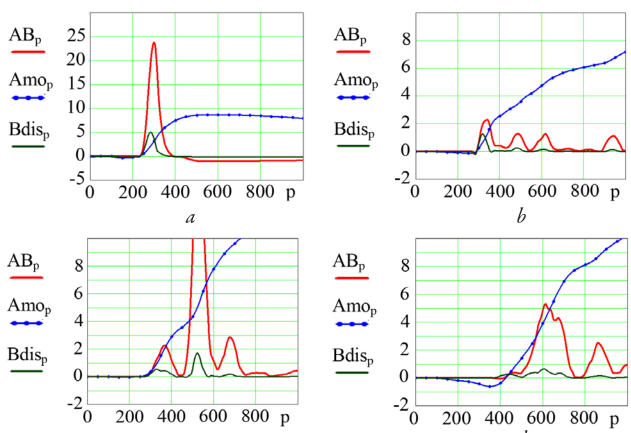

Fig. 1. Results of comparison of the proposed optimal methods for carbon monoxide during ignition of various materials: *a* – alcohol; *b* – paper; *c* – wood; *d* – textiles

Similar results for the specific optical density of smoke are shown in Fig. 2. Experimental results of comparison of the indicated optimal methods for temperature are shown in Fig. 3.

The results of comparison of the optimal II methods for carbon monoxide concentration, specific optical density of smoke and GE temperature indicate the advantages of the II method (13) compared to methods (11) and (12). This is explained by the fact that the optimal method (13) carries out II based on the maximum amount of information contained simultaneously in the sample mean and sample variance of the controlled GE HP. At the same time, the optimality of the proposed II methods is guaranteed by the fact that, unlike the existing II methods, they are obtained based on sufficient statistics in the form of likelihood ratios and the choice of the corresponding optimal threshold. It is shown that the value of the optimal threshold in this case additionally depends on the nonlinear function of the ratio of the variances (accuracies) of the corresponding estimates of the sample moments for the control interval, which depends on the current time, and the training interval of a fixed value, determined by *N*. The training sample should be selected from a fixed interval of reliable absence of I of material. In this case, the value should satisfy the condition of a large sample. In this case, the obtained optimal methods of II can be considered as asymptotic optimal ones, which provide the maximum probability of correct detection of I for a given probability of its false detection (detection error) [19].

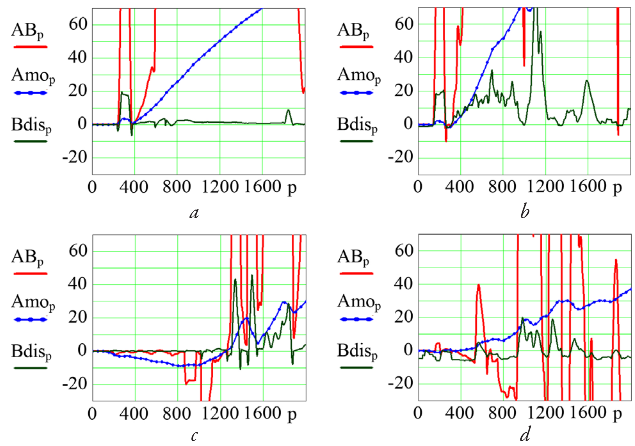

Fig. 2. Results of comparison of the proposed optimal methods for the specific optical density of smoke during ignition of various materials: *a* – alcohol; *b* – paper; *c* – wood; *d* – textiles

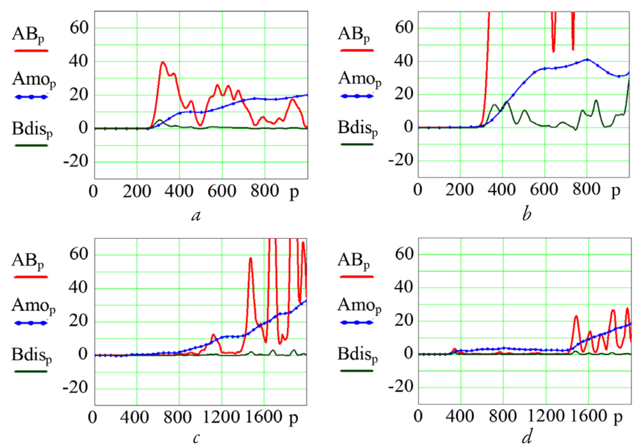

Fig. 3. Results of comparison of the proposed optimal methods for smoke temperature during ignition of various materials: *a* – alcohol; *b* – paper; *c* – wood; *d* – textile

The obtained results in the form of the proposed II methods based on the GE HP control can be used in practice in the development of new means and systems of fire automation, capable of promptly II for preventing fires in the premises of various objects [20].

A limitation of this research is that the results of checking the optimal II methods were carried out in a laboratory chamber, and not in real premises with a real fire load. Therefore, the results of the check should be considered experimental and model.

The martial law conditions in Ukraine led to random power outages during the experiment, which caused the failure of two GE HP control sensors in the laboratory chamber. This required additional financial and time costs for organizing and conducting the experiment.

The prospects for further research are related to a larger-scale verification of the proposed optimal II methods during fire tests in real premises and with different fire loads.

4. Conclusions

The results are obtained based on the synthesis of optimal methods in accordance with the likelihood ratio criterion. A rigorous synthesis was achieved by moving from the space of controlled hazardous parameters of the gas environment to the spaces of sample means, sample variances, and the space of joint sample means and variances. Under the condition of large samples, the distribution of sample means, sample variances, and their joint values tends to the Gaussian distribution. This allows using the likelihood ratio criterion. Unlike the traditional approach, the likelihood ratio is current and is determined relative to a fixed Gaussian distribution in the case of a reliable absence of a fire. It is established that the optimal method for detecting fires based on the joint use of sample means and variances with the same quality indicators surpasses the optimal methods for detecting fires based only on the sample mean or only on the sample variance. This is explained by the fact that the optimal method for detecting fires based on the joint use of sample means and variances uses a larger amount of information contained in the controlled hazardous parameters of the gas environment. The results obtained are useful from a practical point of view of improving existing fire automation equipment and systems in facility premises in order to prevent fires in them.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship or other, which could affect the study and its results presented in this article.

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Data availability

Data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

References

1. Sadkovyi, V., Andronov, V., Semkiv, O., Kovalov, A., Rybka, E., Otrosh, Yu. et al.; Sadkovyi, V., Rybka, E., Otrosh, Yu. (Eds.) (2021). *Fire resistance of reinforced concrete and steel structures.* Kharkiv: PC TECHNOLOGY CENTER, 180. http://doi.org/10.15587/978-617-7319-43-5
2. Popov, O., Kovach, V., Iatsyshyn, A., Lahoiko, A., Ryzhchenko, O., Dement, M. (2023). Features function of radiation monitoring system world's countries of developed nuclear energy. *Studies in Systems, Decision and Control.* Vol. 481. Cham: Springer, 471–497.
3. *World Fire Statistics* (2022). Center for Fire Statistics of CTIF, 27, 65.
4. Gottuk, D. T., Wright, M. T., Wong, J. T., Pham, H. V., Rose-Pehrsson, S. L., Hart, S. et al. (2002). *Prototype early warning fire detection system: test series 4 results.* NRL Ltr Rpt Ser, 6180, 0466.
5. Muhammad, K., Ahmad, J., Mehmood, I., Rho, S., Baik, S. W. (2018). Convolutional Neural Networks Based Fire Detection in Surveillance Videos. *IEEE Access, 6,* 18174–18183. https://doi.org/10.1109/access.2018.2812835
6. Sadkovyi, V., Pospelov, B., Rybka, E., Kreminskyi, B., Yashchenko, O., Bezuhla, Y. et al. (2022). Development of a method for assessing the reliability of fire detection in premises. *Eastern-European Journal of Enterprise Technologies, 3 (10 (117)),* 56–62. https://doi.org/10.15587/1729-4061.2022.259493
7. Wu, Y., Harada, T. (2004). Study on the burning behaviour of plantation wood. *Scientia Silvae Sinicae, 40,* 131.
8. Cheng, C., Sun, F., Zhou, X. (2011). One fire detection method using neural networks. *Tsinghua Science and Technology, 16 (1),* 31–35. https://doi.org/10.1016/s1007-0214(11)70005-0
9. Ding, Q., Peng, Z., Liu, T., Tong, Q. (2014). Multi-Sensor Building Fire Alarm System with Information Fusion Technology Based on D-S Evidence Theory. *Algorithms, 7 (4),* 523–537. https://doi.org/10.3390/a7040523
10. Pospelov, B., Rybka, E., Samoilov, M., Morozov, I., Bezuhla, Y., Butenko, T. et al. (2022). Defining the features of amplitude and phase spectra of dangerous factors of gas medium during the ignition of materials in the premises. *Eastern-European Journal of Enterprise Technologies, 2 (10 (116)),* 57–65. https://doi.org/10.15587/1729-4061.2022.254500
11. Pospelov, B., Rybka, E., Savchenko, A., Dashkovska, O., Harbuz, S., Naden, E. et al. (2022). Peculiarities of amplitude spectra of the third order for the early detection of indoor fires. *Eastern-European Journal of Enterprise Technologies, 5 (10 (119)),* 49–56. https://doi.org/10.15587/1729-4061.2022.265781
12. Pospelov, B., Andronov, V., Rybka, E., Chubko, L., Bezuhla, Y., Gordiichuk, S. et al. (2023). Revealing the peculiarities of average bicoherence of frequencies in the spectra of dangerous parameters of the gas environment during fire. *Eastern-European Journal of Enterprise Technologies, 1 (10 (121)),* 46–54. https://doi.org/10.15587/1729-4061.2023.272949
13. McGrattan, K., Hostikka, S., McDermott, R., Floyd, J., Weinschenk, C., Overholt, K. (2016). *Fire dynamics simulator technical reference guide.* National Institute of Standards and Technology, 3, 6.
14. Dubinin, D., Cherkashyn, O., Maksymov, A., Beliuchenko, D., Hovalenkov, S., Shevchenko, S., Avetisyan, V. (2020). Investigation of the effect of carbon monoxide on people in case of fire in a building. *Sigurnost, 62 (4),* 347–357. https://doi.org/10.31306/s.62.4.2
15. Floyd, J., Forney, G., Hostikka, S., Korhonen, T., McDermott, R., McGrattan, K. (2013). *Fire Dynamics Simulator (Version 6) User's Guide.* National Institute of Standard and Technology, 1, 1.
16. Optical/Heat Multisensor Detector (2019). *Discovery.*
17. Hulse, L. M., Galea, E. R., Thompson, O. F., Wales, D. (2020). Perception and recollection of fire hazards in dwelling fires. *Safety Science, 122,* 104518. https://doi.org/10.1016/j.ssci.2019.104518
18. Dragotti, P. L., Vetterli, M., Blu, T. (2007). Sampling Moments and Reconstructing Signals of Finite Rate of Innovation: Shannon Meets Strang-Fix. *IEEE Transactions on Signal Processing, 55 (5),* 1741–1757. https://doi.org/10.1109/tsp.2006.890907
19. Cramér, H. (1999). *Mathematical methods of statistics.* Princeton university press, 26.
20. Otrosh, Y., Rybka, Y., Danilin, O., Zhuravskyi, M. (2019). Assessment of the technical state and the possibility of its control for the further safe operation of building structures of mining facilities. *E3S Web of Conferences, 123,* 01012. https://doi.org/10.1051/e3sconf/201912301012

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