

This paper reports the rationale for the modification of Brown's zero-order model, which ensures increased accuracy of the short-term fire forecast based on the use of the current measure of recurrence in the increments of the state of the air environment in the premises. A special feature of the proposed model modification is that the a priori model of the dynamics of the level of the time series of the measure of the current recurrence of increments in the air environment states determined by the dangerous factors of the fire has been modified. In this case, it is proposed that the new a priori model should take into consideration additionally the value of the current increments of the level of the studied time series. That makes it possible to negligibly reduce errors of the short-term forecast of fire in the premises without significantly complicating Brown's zero-order model while retaining all its implementing advantages. The provided accuracy of the forecast for one step in advance on the basis of a time series of measures of the current recurrence of increments of the state of the air environment, determined from the experimental data during the ignition of alcohol and timber in a laboratory chamber, has been investigated. The considered quantitative indicators of forecast accuracy are the absolute and average errors exponentially smoothed with a parameter of 0.4. It has been established that for the proposed modification the value of the average absolute error does not exceed 0.02 %. That means that an error of the short-term forecast of a fire in the premises based on the proposed modification is an order of magnitude less than that in the case of using known Brown's model at the smoothing parameter from an unclustered set. The results from the ignition of alcohol and timber in the laboratory chamber, in general, indicate significant advantages of using the proposed modification of Brown's zero-order model for a short-term forecast of a fire in the premises

Keywords: fire forecast, Brown's model modification, ignition, current recurrence measure, state vector increment

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SHORT-TERM FORECAST OF FIRE IN THE PREMISES BASED ON MODIFICATION OF THE BROWN'S ZERO-ORDER MODEL

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1. Introduction

Every year, fires in the premises take more than 90 thousand human lives. The fire start is always preceded by the

ignition of combustible material [1]. Along with fires in ecosystems [2] and at production sites [3, 4], the most dangerous are indoor fires (IFs) [5]. First, such fires are the most frequent, second, IFs cause a significant threat to human life

and health [6]. Third, IFs violate the integrity and stability of objects [7], as well as the existing balance in the natural environment [8]. In 2019, in the U.S., IF was reported every 93 seconds. Moreover, every 3 hours there was a death of a person. Material damage from IFs is estimated at about USD 12.3 billion [9]. Given that the United States pays serious attention to protection against IFs, such statistics indicate the insufficient effectiveness of existing measures and technologies for the prevention of IFs. That indicates the special relevance of the task of protecting premises from fire. One of the rational directions for resolving this issue at present is the implementation of a short-term forecast (STF) of IF occurrence. The IF STF would make it possible to time detect the onset of ignition of combustible material and prevent the escalation of ignition into uncontrolled fires.

2. Literature review and problem statement

Paper [10] outlines methods of IF forecasting. However, known methods to forecast IFs are based on the deterministic models of the dynamics of the main fire hazards (MFHs). Issues related to the STF of fires in actual premises are neither considered nor resolved. These methods make it possible to describe a deterministic change in the parameters of the environment, taking into consideration the characteristics of premises over time [11]. That means that such IF methods are intended only for modeling fires in specific premises at the stage of planning fire prevention measures and cannot be used for the purpose of operational IF STF under actual conditions. At the same time, the real conditions for the occurrence of IFs are characterized by the rather complex and individual dynamics of the state of the air environment in premises (AEPs). That explains the impossibility of applying known methods for predicting fires in actual premises.

In [12], it is noted that the actual AEP during IF is a complex dynamic system that has the properties of dissipative structures, the nonlinearity of the dynamics of states with elements of self-organization. It is not possible to identify complex relationships in such a system based on known linear methods. This leads to significant errors in assessing the actual dynamics of the state of AEP, which does not allow for the STF of IFs [13]. At the same time, [14] notes that the nature of the current dynamics of the state of AEP is of paramount importance for IF STF. More rational for IF STF are the methods of nonlinear dynamics, designed to analyze the dynamic properties of various systems [15]. Quantitative methods for analyzing the nonlinear dynamics of complex systems under non-stationary conditions are considered in [16]. The application of those methods in geophysics is described in [17]. However, in [15–17], the methods of IF STF based on the analysis of the state of AEP in actual premises are not considered and investigated. At the same time, a series of works consider experimental studies into the ignition of combustible materials in the premises. Thus, in [18], the characteristics of the process of IF occurrence are experimentally investigated. The results of studying the effect of thermal radiation on the rate of heat generation for various materials are reported in [19]. An experimental study of the combustion mode of various materials under the influence of external heat flux was performed in [20]. A detailed study of the rate of heat generation in AEP during a fire is reported in work [21]. It is noted that the

dynamics of the state of AEP at the initial stage of the occurrence of IF are complex and non-stationary. Improving the efficiency of IF detection systems based on known methods is addressed in [22]. At the same time, new methods of IF STF based on the analysis of the dynamics of the state of AEP are not considered and investigated [23]. In [24], under non-stationary conditions of AEP, it is proposed to apply self-adjusting methods for detecting early fires. The main limitation of those methods is that they are based on the average values of individual parameters of the AEP state. The study of the dynamics of temporary autocorrelations and pairwise correlations of individual components of the AEP state in a model chamber is performed in [25]. It is noted that for the reliable detection of fires, the current states of AEP should be considered more important, rather than their temporal correlations. Methods suitable for detecting indoor fires, based on the parameters of the current state of AEP, are considered in [26]. However, those methods are valid only for stationary AEP states and are based on the averaged AEP status indicators. That does not allow them to be used for IF STF. The use of temporal and frequency changes in AEP states to identify IFs is considered in [27]. It is noted that due to complexity the issue of the frequency-time detection of fires based on the dynamics of AEP states remains unresolved. At the same time, it is shown that the known methods are unsuitable for IF STF. A method to detect ignition under the conditions of non-stationary nature of AEP states is proposed in [28]. However, the method is based on the Fourier transform to the stationary fragments of the non-stationary dynamics of AEP states. In practice, in the case of IF, it is difficult to isolate stationary fragments in the non-stationary dynamics of AEP states. Paper [29] reports the results of an experimental study into the dynamics of only the combustion rate of various materials in enclosed and ventilated rooms. No features in the dynamics of the states of AEP were investigated. It should be noted that the main limitation of the methods considered above is the clear neglect of the systematic approach in the detection of fires. That means that AEP during IF is not considered as some single complex nonlinear dynamic system. The dynamics of AEP states are not investigated or predicted. The dynamics of increments of individual parameters of the state of AEP are explored in [30]. It is noted that the dynamics of increments in the state of AEP can be considered as an effective attribute for identifying early fires and implementing the IF STF. At the same time, the results of the research are limited to the traditional statistics on increments. The application of methods of the frequency-time identification of nonlinear dynamical systems to identify the specified features of AEP is considered in [31, 32]. In [33], the possibility of applying the method of short-term Fourier transform to detect IFs is examined. However, the methods in [31–33] are quite difficult to implement and cannot be considered as rational for the implementation of IF STF under actual conditions. The use of a frequency-time method to assess the dynamics of the state of AEP during ignition is reported in [34]. The method is quite difficult to implement and has insufficient efficiency for the implementation of IF STF. Paper [35] proposes a method for operational forecasting of IF under actual conditions, which is based on the representation of AEP in the form of some complex dynamic system whose state is estimated by the vector of MFH. At the same time, for the implementation of IF STF, it is proposed to use Brown's zero-order model for a current recurrence measure for the

increments of the AEP states. Features of the application of a given model for IF STF is that it is valid for time series (TS) with the random level dynamics without signs of short trends. At the same time, the quality of the forecast is completely determined by the value of the exponential smoothing parameter [36]. In [37], the classical set for the value of the smoothing parameter is proposed to be expanded to an unclustered set in order to give the exponential smoothing and the corresponding Brown's model the capability to predict TS levels with random short non-stationary trends. Paper [38] reports a study into the quality of IF STF based on the use of Brown's zero-order model for the parameter of exponential smoothing from the classical and unclustered sets. It is confirmed that in the case of an unclustered set, the quality of IF STF increases. However, the quality of IF STF is limited to the applied Brown's model with exponential smoothing for the simplest predefined series-level model. At the same time, no possible modification of Brown's zero-order model to improve the quality of IF STF was proposed.

Thus, it has been established that the dynamics of the AEP states during IFs have a complex nonlinear character, depending on the actual conditions of fires and determined by a set of unknown and time-dependent MFHs. To detect fires, most known methods are quite difficult to implement, they have limited sensitivity and efficiency, and their use for IF STF is problematic.

More promising and rational are methods based on the methods of nonlinear dynamics [36, 38]. Preferred for the implementation of IF STF are forecasting methods based on Brown's zero-order model [36] or its modifications. In this regard, an important and unresolved part of the task to ensure IF STF is the appropriate modification of Brown's zero-order model.

3. The aim and objectives of the study

The aim of this work is to devise a modification of Brown's zero-order model in order to ensure the increased accuracy of the short-term fire forecast for a current recurrence measure of the increments of the state of the air environment in the premises.

To accomplish the aim, the following tasks have been set:

- to substantiate the modification of the Brown's zero-order model, which provides for the increased accuracy of short-term fire forecast based on the use of a current recurrence measure of increments of the state of the air environment in the premises;
- to investigate prediction errors one step in advance based on the developed modification of Brown's zero-order model when alcohol and timber are ignited in a laboratory chamber.

4. The study materials and methods

The object of the study was the IF STF based on the proposed modification of Brown's zero-order model. The subject of the research was the dynamics of STF errors, characterized by the exponentially smoothed (a parameter of 0.4) values for the current absolute and average STF errors. The materials used, the research methods and the procedure are described in detail in work [38]. We studied the accuracy of IF STF one step in advance using the proposed modification of

Brown's zero-order model and exponential smoothing based on experimental data. The experiment involved the ignition of test materials in the form of alcohol and timber, which have different rates of ignition, in a laboratory chamber that simulates a non-airtight room. At the same time, the quantitative assessment of STF accuracy involved determining the exponentially smoothed current absolute (MAE) and average (ME) forecast errors. The measured data were acquired and processed on a PC employing the specialized developed software that allows the automatic registration of measured data, as well as a software application in the Mathcad 14 programming environment (USA).

5. The results of modifying Brown's zero-order model for fire prediction

5.1. Substantiating the modification of Brown's zero-order model

Various mathematical models are used to predict TS. In a general case, these models can be represented as an additive mixture of some function. Such a function describes the combined effect of a set of known or unknown factors on the value of the studied TS, and a random uncorrelated process with a zero mean and finite. At the same time, these components of the mixture differ in the nature of the influence on the current TS values. The random component affects only the current values of the series synchronous with it. The function of influencing factors reflects the influence of one, two, or all previous terms of TS. This means that it is through this function that TS terms interact up to the current point in time. Therefore, this function contains all the information necessary for forecasts. However, it should be noted that the known concepts of the trend are quite contradictory [39]. Each definition typically characterizes a particular way of assessing the trend, rather than its nature or its essence. Often, a trend is understood only as a deterministic component of TS. That limits the use of a given term for non-stationary TS. It should be noted that the above additive components of the original TS are unobservable. Therefore, the identification of these components is the main task of analyzing and forecasting TS. At the same time, the tasks of analysis and forecasting are traditionally solved in relation to the corresponding models. A predictive model is typically some approximation of the TS trend. In this case, the forecasts are estimates of future levels of TS, and their sequence for different points in time is an assessment of the dynamics of the trend of the analyzed BP. Usually, when building predictive models, an appropriate hypothesis is put forward about the expected dynamics of the TS trend. Since the validity of any hypothesis is always relative, adaptive predictive models have the greatest capabilities. Such models are able to independently correct the initial hypothesis, based on the provision of greater forecast accuracy for the investigated TS.

Due to the particular risk of IF occurrence, the class of adaptive predictive models that provide STF is important. It should be borne in mind that the dynamics of the level of TS for MFH are random and non-stationary in nature without traditional signs of trend and seasonality.

The simplest TS model for this case is described in the following form:

$$s_i = T_i + n_i, \quad (1)$$

where T_i is the time-resolved random TS level of MFH at an arbitrary discrete moment i ; n_i is the value of random noise at the discrete moment i having a Gaussian distribution with a zero mean at variance σ^2 .

Taking into consideration representation (1), Brown's model is defined in the following form:

$$P_i(d) = \hat{T}_i, \quad (2)$$

where $P_i(d)$ is the forecast of the TS level (1) by the value of step d forward, at moment i ; \hat{T}_i is the estimation, time-dependent, of the level of TS (1) of MFH at moment i .

In Brown's model (2), the typically used estimate \hat{T}_i of the series level in (1) is usually the exponentially smoothed mean of the current values of TS (1), determined from the following recurrent formula [40, 41]:

$$\hat{T}_i = h s_i + (1-h) \hat{T}_{i-1}, \quad (3)$$

where \hat{T}_i is the exponentially smoothed mean of the current values of TS (1) at moment i ; h is the value of the exponential smoothing parameter; s_i is the value of the current value of TS (1) at moment i ; \hat{T}_{i-1} is the exponentially smoothed mean of the current values of TS (1) at the moment $i-1$.

The advantage of Brown's model (2) taking into consideration (3) is simplicity, as well as the ability to adapt the model to the uncertain dynamics of the TS level. At the same time, a given model is based on the use of only exponentially smoothed average level of the studied TS whose characteristic depends on the smoothing parameter h . This means that the accuracy (error) of forecast (2) would be fully determined by the accuracy (error) in the exponential smoothing of TS.

The recurrent formula of exponential smoothing (3) can be represented in the equivalent form:

$$\hat{T}_i = \hat{T}_{i-1} + h(s_i - \hat{T}_{i-1}). \quad (4)$$

Expression (4) defines the known recurrent formula of the Kalman filter for s_i observations. The value of the parameter h in (4) depends on the discrete moment i of the observation time. Therefore, formula (4) generally describes a non-stationary Kalman filter. The current value of the h parameter, in this case, determines the non-stationary gain of filter (4). At the same time, in the class of linear devices, the Kalman filter produces the absolute best estimate. However, these advantages of the Kalman filter (4) are valid only for the observation equation (1), in which the current level of the series satisfies the following equation:

$$T_i = T_{i-1}. \quad (5)$$

Model (5) means that the value of the current level of TS of MFH is random but constant. It is believed that the initial value of the random level of the series T_0 is distributed according to Gauss with a mathematical expectation T_0 and a predefined variance. The value of the exponential smoothing parameter in (3) determines not only the characteristics of Brown's zero-order model but also the adaptive properties of this model [42]. In this regard, a known modification of Brown's zero-order model concerns the procedure of exponential smoothing in order to expand its use to non-stationary TS. This modification is associated with the expansion of the classical set for the exponential smoothing

parameter in (3) in the case of an unclustered set [43]. In line with (4), the fixed value h from the classical set would match a quasi-optimal Kalman filter with a stationary gain factor for the case when the variance of the TS level does not exceed the variance of the observation noise in (1). In this case, the fixed value of the parameter h from the unclustered set would match a quasi-optimal Kalman filter with a stationary gain factor corresponding to the case when the variance of the TS level exceeds the dispersion of observation noise in (1).

The main limitation of the known Brown's zero-order model for IF STF is that the level of the TS being studied is determined by model (5). In this case, it is proposed using, as TS, the TS of the current estimates of the recurrence of increments of the AEP state vector [35]. The dynamics of the level of such TS differs significantly in the case of fires from model (5). Modifying the known Brown's model by applying the parameter h from the unclustered set partially solves the task of IF STF. However, the model of the dynamics of the level of the studied TS remains in the form of (5). Such a model is rough enough to reflect the features of the dynamics of the TS level of the current estimates of the recurrence of increments of the AEP state vector [43, 44]. In some cases, a combination of actual factors can cause both an increase and a decrease in the value of the current recurrence of increments of AEP state. At the same time, there may be an alternation of these situations.

In this regard, it is proposed to modify model (5) in the following form:

$$T_i = T_{i-1} + T_{i-1} - T_{i-2}. \quad (6)$$

Model (6), in contrast to model (5), takes into consideration not only the current level of the series but also their increments. Therefore, the recurrent formula of exponential smoothing (4), considering (6), would take the following form:

$$\hat{T}_i = \hat{T}_{i-1} + \hat{T}_{i-1} - \hat{T}_{i-2} + h(s_i - \hat{T}_{i-1} + \hat{T}_{i-1} - \hat{T}_{i-2}). \quad (7)$$

Ratio (7) would determine the proposed modification of the known Brown's zero-order model. This modification concerns the exponential smoothing procedure in the form of an appropriate Kalman filter for the model of the dynamics of the level of the TS under study (6). In this case, the smoothing parameter h for the optimal Kalman filter (7) would be determined from the corresponding dynamic equations for the gain factor of the Kalman filter, allowing it to be calculated on the basis of a priori data without using measurements. However, in practice, instead of the optimal Kalman filter that is difficult to implement, it is easier to use its quasi-optimal version for a stationary gain factor value. At the same time, the loss in the accuracy of the assessment is insignificant. Therefore, the proposed modification of the Brown's zero-order model for IF STF refers only to its exponential smoothing procedure in the form of a quasi-optimal Kalman filter.

5. 2. Investigating forecast errors based on the devised modification of Brown's zero-order model

Fig. 1 shows the characteristic dynamics of MAE and ME STF for the proposed modification of Brown's zero-order model at $h=0.99$ (green plots) for the case of alcohol ignition in a laboratory chamber. There are also dependences for known modification at h values of 0.2 (red plots) and 1.2 (blue plots).

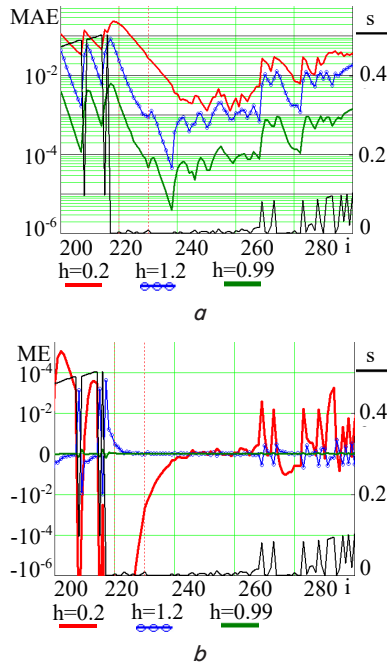


Fig. 1. Dynamics of forecast errors for the case of alcohol ignition: *a* – current absolute errors; *b* – average errors

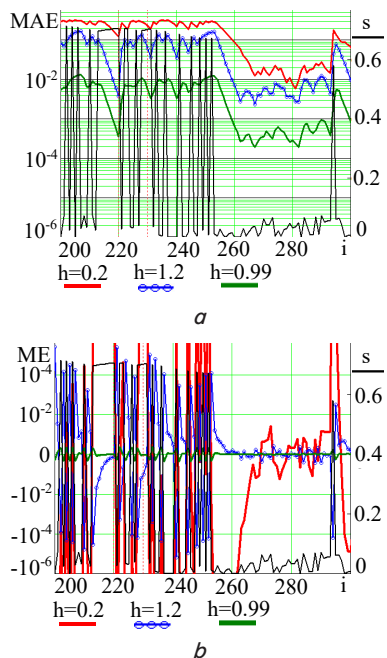


Fig. 2. Dynamics of forecast errors for the case of timber ignition: *a* – current absolute errors; *b* – average errors

In Fig. 1, 2, black color shows the dynamics of the measure of the current recurrence of the air environment states in a chamber for the corresponding tested combustible materials.

6. Discussion of results of studying the modification of Brown's zero-order model

The results of our study into the dynamics of STF errors during the ignition of alcohol and timber, illustrated in Fig. 1, 2, are explained by the various possibilities of modifying Brown's zero-order model to carry out IF STF. A known

modification reported in [38] indicates that the unclustered set for the smoothing parameter makes it possible to predict non-stationary current measures of recurrence of increments of the AEP state vector quite effectively. For example, the investigated errors related to STF for materials with different rates of ignition are about an order of magnitude smaller for the unclustered set of the exponential smoothing parameter compared to the classical set. The proposed modification of the Brown's zero-order model, based on a change in the a priori model of the dynamics of the series level, makes it possible to reduce the errors in STF by an order of magnitude in comparison with the case of exponential smoothing with a parameter from the unclustered set. At the same time, the obtained STF errors for a known modification, determined by MAE and ME, indicate their difference for both the same and different combustible materials under consideration. Thus, for alcohol, the value of MAE and ME in the case of the classical smoothing parameter provides an error in STF within an interval of the absence of ignition, not exceeding 20%. In this case, for the smoothing parameter from an unclustered set, an order of magnitude smaller STF error is provided within the specified interval. This is especially true for moments in time, for which the values of the measure of the current recurrence of the increments of the state of the medium in a chamber are large. Similar patterns are characteristic of the ignition of timber. In the case of the proposed modification of the forecast model, the values of MAE and ME are an order of magnitude smaller compared to the case of the unclustered smoothing parameter. This means that the proposed modification makes it possible to ensure the accuracy of STF with errors not exceeding 0.02%.

In the transition zone corresponding to the moment of ignition of materials, the value of MAE for alcohol corresponds to the STF error, approximately equal to 2% for the smoothing parameter from the classical set, and 0.2% for the case involving an unclustered set. In addition, the dynamics of MAE in the transition zone indicates a higher accuracy of STF at the beginning of the transition zone for the case of the unclustered parameter in Brown's model. At the same time, for the proposed modification of Brown's model, the value of MAE does not exceed 0.02%. That means that the error of IF STF, in accordance with the proposed modification, is ensured to be an order of magnitude less than that in the case of using a smoothing parameter from the unclustered set. In this case, significantly lower values of STF ME for the ignition of alcohol and timber are also provided.

Thus, the experimental data reported here generally indicate a significant advantage of the proposed modernization of Brown's zero-order model while preserving all the practical advantages of this model. The limitations of our study include the fact that the results were obtained on the basis of experimental data on the state of the air environment in a laboratory chamber during the ignition of alcohol and timber. It should be noted that the results obtained were influenced by the parameters of the chamber, the size of the ignition site, and the positioning of measuring sensors relative to the site. Therefore, for IF STF, in accordance with the proposed modification, it is advisable to position the measuring sensors of AEP MFH in areas where the probability of fore occurrence is maximal.

Possible ways to advance this study include the expansion of experimental studies for various types of premises and fire loads in them. During the extended experimental studies, it would be necessary to assess the practical limits of applicability and limitations of the proposed modification of Brown's zero-order model for IF STF.

7. Conclusions

1. We have substantiated the modification of Brown's zero-order model, which provides for the increased accuracy of the short-term fire forecast based on the use of the current measure of recurrence of increments of the state of the air environment in the premises. The proposed modification essentially implies the proposal to modify the a priori model of the dynamics of the level of the time series of the measure of the current recurrence of increments of air environment conditions determined by fire hazards. In this case, it is proposed that a priori model should take into consideration additionally the value of the current increments of the level of the studied series. That makes it possible to render the prediction errors negligible without significantly complicating Brown's zero-order model while retaining all its implementing advantages.

2. The predictive accuracy of the forecast one step in advance on the basis of the time series of the measure of the current recurrence of increments of the state of the air environment provided by the proposed modification of Brown's zero-order model order has been investigated. To this end, we used the experimental data on igniting alcohol and timber in a laboratory chamber. As quantitative indicators of forecast accuracy, absolute and average forecast errors exponentially smoothed with a parameter of 0.4 have been considered. It was established that for the proposed modification the value of the average absolute error does not exceed 0.02 %. That means that the prediction error based on the proposed modification of the model is less by an order of magnitude than that in the case of using a known model with the smoothing parameter from an unclustered set. Thus, the results reported here generally indicate significant advantages of using the proposed modification of Brown's zero-order model for the short-term forecasting of fire in the premises.

References

1. Kustov, M. V., Kalugin, V. D., Tutunik, V. V., Tarakhno, E. V. (2019). Physicochemical principles of the technology of modified pyrotechnic compositions to reduce the chemical pollution of the atmosphere. *Voprosy Khimii i Khimicheskoi Tekhnologii*, 1, 92–99. doi: <https://doi.org/10.32434/0321-4095-2019-122-1-92-99>
2. Migalenko, K., Nuianzin, V., Zemlianskiy, A., Dominik, A., Pozdieiev, S. (2018). Development of the technique for restricting the propagation of fire in natural peat ecosystems. *Eastern-European Journal of Enterprise Technologies*, 1 (10 (91)), 31–37. doi: <https://doi.org/10.15587/1729-4061.2018.121727>
3. Vambol, S., Vambol, V., Kondratenko, O., Koloskov, V., Suchikova, Y. (2018). Substantiation of expedience of application of high-temperature utilization of used tires for liquefied methane production. *Journal of Achievements in Materials and Manufacturing Engineering*, 2 (87), 77–84. doi: <https://doi.org/10.5604/01.3001.0012.2830>
4. Vambol, S., Vambol, V., Sobyna, V., Koloskov, V., Poberezhna, L. (2018). Investigation of the energy efficiency of waste utilization technology, with considering the use of low-temperature separation of the resulting gas mixtures. *Energetika*, 64 (4). doi: <https://doi.org/10.6001/energetika.v64i4.3893>
5. Semko, A., Rusanova, O., Kazak, O., Beskrovnaya, M., Vinogradov, S., Gricina, I. (2015). The use of pulsed high-speed liquid jet for putting out gas blow-out. *The International Journal of Multiphysics*, 9 (1), 9–20. doi: <https://doi.org/10.1260/1750-9548.9.1.9>
6. Vambol, S., Vambol, V., Kondratenko, O., Suchikova, Y., Hurenko, O. (2017). Assessment of improvement of ecological safety of power plants by arranging the system of pollutant neutralization. *Eastern-European Journal of Enterprise Technologies*, 3 (10 (87)), 63–73. doi: <https://doi.org/10.15587/1729-4061.2017.102314>
7. Otrosh, Y., Kovalov, A., Semkiv, O., Rudeshko, I., Diven, V. (2018). Methodology remaining lifetime determination of the building structures. *MATEC Web of Conferences*, 230, 02023. doi: <https://doi.org/10.1051/mateconf/201823002023>
8. Vasyukov, A., Loboichenko, V., Bushtec, S. (2016). Identification of bottled natural waters by using direct conductometry. *Ecology, Environment and Conservation*, 22 (3), 1171–1176.
9. Ahrens, M., Evarts, B. (2020). Fire loss in the United States during 2019. National Fire Protection Association, 11. Available at: <https://www.nfpa.org/~media/fd0144a044c84fc5baf90c05c04890b7.ashx>
10. Koshmarov, Yu. A., Puzach, S. V., Andreev, V. V. (2012). *Prognozirovaniye opasnykh faktorov pozhara v pomeschenii*. Moscow: AGPS MChS Rossii, 126.
11. Otrosh, Y., Semkiv, O., Rybka, E., Kovalov, A. (2019). About need of calculations for the steel framework building in temperature influences conditions. *IOP Conference Series: Materials Science and Engineering*, 708, 012065. doi: <https://doi.org/10.1088/1757-899x/708/1/012065>
12. Pospelov, B., Andronov, V., Rybka, E., Meleshchenko, R., Borodych, P. (2018). Studying the recurrent diagrams of carbon monoxide concentration at early ignitions in premises. *Eastern-European Journal of Enterprise Technologies*, 3 (9 (93)), 34–40. doi: <https://doi.org/10.15587/1729-4061.2018.133127>
13. Andronov, V., Pospelov, B., Rybka, E., Skliarov, S. (2017). Examining the learning fire detectors under real conditions of application. *Eastern-European Journal of Enterprise Technologies*, 3 (9 (87)), 53–59. doi: <https://doi.org/10.15587/1729-4061.2017.101985>
14. Ahn, C.-S., Kim, J.-Y. (2011). A study for a fire spread mechanism of residential buildings with numerical modeling. *Safety and Security Engineering IV*. doi: <https://doi.org/10.2495/safe110171>
15. Webber, C. L., Ioana, C., Marwan, N. (Eds.) (2016). Recurrence plots and their quantifications: expanding horizons. *International Symposium on Recurrence Plots*. Grenoble, 380. doi: <https://doi.org/10.1007/978-3-319-29922-8>
16. Sadkovyi, V., Pospelov, B., Andronov, V., Rybka, E., Krainiukov, O., Rud, A. et. al. (2020). Construction of a method for detecting arbitrary hazard pollutants in the atmospheric air based on the structural function of the current pollutant concentrations. *Eastern-European Journal of Enterprise Technologies*, 6 (10 (108)), 14–22. doi: <https://doi.org/10.15587/1729-4061.2020.218714>
17. Turcotte, D. L. (1997). *Fractals and chaos in geology and geophysics*. Cambridge University Press. doi: <https://doi.org/10.1017/cbo9781139174695>

18. Poulsen, A., Jomaas, G. (2011). Experimental Study on the Burning Behavior of Pool Fires in Rooms with Different Wall Linings. *Fire Technology*, 48 (2), 419–439. doi: <https://doi.org/10.1007/s10694-011-0230-0>
19. Zhang, D., Xue, W. (2010). Effect of heat radiation on combustion heat release rate of larch. *Journal of West China Forestry Science*, 39, 148.
20. Ji, J., Yang, L., Fan, W. (2003). Experimental Study on Effects of Burning Behaviours of Materials Caused by External Heat Radiation. *Journal of Combustion Science and Technology*, 9, 139.
21. Peng, X., Liu, S., Lu, G. (2005). Experimental Analysis on Heat Release Rate of Materials. *Journal of Chongqing University*, 28, 122.
22. Andronov, V., Pospelov, B., Rybka, E. (2017). Development of a method to improve the performance speed of maximal fire detectors. *Eastern-European Journal of Enterprise Technologies*, 2 (9 (86)), 32–37. doi: <https://doi.org/10.15587/1729-4061.2017.96694>
23. Pospelov, B., Andronov, V., Rybka, E., Meleshchenko, R., Gornostal, S. (2018). Analysis of correlation dimensionality of the state of a gas medium at early ignition of materials. *Eastern-European Journal of Enterprise Technologies*, 5 (10 (95)), 25–30. doi: <https://doi.org/10.15587/1729-4061.2018.142995>
24. Pospelov, B., Andronov, V., Rybka, E., Skliarov, S. (2017). Design of fire detectors capable of self-adjusting by ignition. *Eastern-European Journal of Enterprise Technologies*, 4 (9 (88)), 53–59. doi: <https://doi.org/10.15587/1729-4061.2017.108448>
25. Pospelov, B., Rybka, E., Meleshchenko, R., Gornostal, S., Shcherbak, S. (2017). Results of experimental research into correlations between hazardous factors of ignition of materials in premises. *Eastern-European Journal of Enterprise Technologies*, 6 (10 (90)), 50–56. doi: <https://doi.org/10.15587/1729-4061.2017.117789>
26. Bendat, J. S., Piersol, A. G. (2010). *Random data: analysis and measurement procedures*. John Wiley & Sons. doi: <https://doi.org/10.1002/9781118032428>
27. Shafi, I., Ahmad, J., Shah, S. I., Kashif, F. M. (2009). Techniques to Obtain Good Resolution and Concentrated Time-Frequency Distributions: A Review. *EURASIP Journal on Advances in Signal Processing*, 2009 (1). doi: <https://doi.org/10.1155/2009/673539>
28. Singh, P. (2016). Time-frequency analysis via the fourier representation. HAL, 1–8. Available at: <https://hal.archives-ouvertes.fr/hal-01303330/document>
29. Pretrel, H., Querre, P., Forestier, M. (2005). Experimental Study Of Burning Rate Behaviour In Confined And Ventilated Fire Compartments. *Fire Safety Science*, 8, 1217–1228. doi: <https://doi.org/10.3801/iafss.fss.8-1217>
30. Pospelov, B., Andronov, V., Rybka, E., Popov, V., Romin, A. (2018). Experimental study of the fluctuations of gas medium parameters as early signs of fire. *Eastern-European Journal of Enterprise Technologies*, 1 (10 (91)), 50–55. doi: <https://doi.org/10.15587/1729-4061.2018.122419>
31. Stankovic, L., Dakovic, M., Thayaparan, T. (2014). *Time-frequency signal analysis*. Kindle edition, 655.
32. Avargel, Y., Cohen, I. (2010). Modeling and Identification of Nonlinear Systems in the Short-Time Fourier Transform Domain. *IEEE Transactions on Signal Processing*, 58 (1), 291–304. doi: <https://doi.org/10.1109/tsp.2009.2028978>
33. Giv, H. H. (2013). Directional short-time Fourier transform. *Journal of Mathematical Analysis and Applications*, 399 (1), 100–107. doi: <https://doi.org/10.1016/j.jmaa.2012.09.053>
34. Pospelov, B., Andronov, V., Rybka, E., Popov, V., Semkiv, O. (2018). Development of the method of frequencytemporal representation of fluctuations of gaseous medium parameters at fire. *Eastern-European Journal of Enterprise Technologies*, 2 (10 (92)), 44–49. doi: <https://doi.org/10.15587/1729-4061.2018.125926>
35. Pospelov, B., Andronov, V., Rybka, E., Samoilo, M., Krainiukov, O., Biryukov, I. et. al. (2021). Development of the method of operational forecasting of fire in the premises of objects under real conditions. *Eastern-European Journal of Enterprise Technologies*, 2 (10 (110)), 43–50. doi: <https://doi.org/10.15587/1729-4061.2021.226692>
36. Sinaga, H., Irawati, N. (2020). A Medical Disposable Supply Demand Forecasting By Moving Average And Exponential Smoothing Method. *Proceedings of the Proceedings of the 2nd Workshop on Multidisciplinary and Applications (WMA) 2018*, 24-25 January 2018, Padang, Indonesia. doi: <https://doi.org/10.4108/eai.24-1-2018.2292378>
37. Svetun'kov, S. G. (2002). O rasshirenii granits primeneniya metoda Brauna. *Izvestiya Sankt-Peterburgskogo gosudarstvennogo universiteta ekonomiki i finansov*, 3, 94–107.
38. Pospelov, B., Rybka, E., Meleshchenko, R., Krainiukov, O., Biryukov, I., Butenko, T. et. al. (2021). Short-term fire forecast based on air state gain recurrence and zero-order Brown model. *Eastern-European Journal of Enterprise Technologies*, 3 (10 (111)), 27–33. doi: <https://doi.org/10.15587/1729-4061.2021.233606>
39. Chetyrkin, E. M. (1977). *Statisticheskie metody prognozirovaniya*. Moscow: Statistika, 200.
40. Marwan, N. (2011). How to avoid potential pitfalls in recurrence plot based data analysis. *International Journal of Bifurcation and Chaos*, 21 (04), 1003–1017. doi: <https://doi.org/10.1142/s0218127411029008>
41. Webber, Jr. C. L., Zbilut, J. P.; Riley, M. A., Van Orden, G. C. (Eds.) (2005). Chapter 2. Recurrence quantification analysis of nonlinear dynamical systems. *Tutorials in contemporary nonlinear methods for the behavioral sciences*, 26–94. Available at: <https://www.nsf.gov/pubs/2005/nsf05057/nmbs/nmbs.pdf>
42. Orlova, I. V., Polovnikov, V. A. (2010). *Ekonomiko-matematicheskie metody i modeli: komp'yuternoe modelirovanie*. Moscow: INFRA-M, 366.
43. Pospelov, B., Rybka, E., Togobytska, V., Meleshchenko, R., Danchenko, Y., Butenko, T. et. al. (2019). Construction of the method for semi-adaptive threshold scaling transformation when computing recurrent plots. *Eastern-European Journal of Enterprise Technologies*, 4 (10 (100)), 22–29. doi: <https://doi.org/10.15587/1729-4061.2019.176579>
44. Pospelov, B., Andronov, V., Rybka, E., Krainiukov, O., Karpets, K., Pirohov, O. et. al. (2019). Development of the correlation method for operative detection of recurrent states. *Eastern-European Journal of Enterprise Technologies*, 6 (4 (102)), 39–46. doi: <https://doi.org/10.15587/1729-4061.2019.187252>