SHORT-TERM FIRE FORECAST BASED ON AIR STATE GAIN RECURRENCE AND ZERO-ORDER BROWN MODEL

Possibilities of parameterization of the zero-order Brown model for indoor air forecasting based on the current measure of air state gain recurrence are considered. The key to the zero-order parametric Brown forecasting model is the selection of the smoothing parameter, which characterizes forecast adaptability to the current air state gain recurrence measure. It is shown that for effective short-term indoor fire forecast, the Brown model parameter must be selected from the out-of-limit set defined by 1 and 2. The out-of-limit set for the Brown model parameter is an area of effective fire forecasting based on the measure of current indoor air state gain recurrence. Errors of fire forecast based on the parameterized zero-order Brown model in the case of the classical and out-of-limit sets of the model parameters are investigated using the example of ignition of various materials in a laboratory chamber. As quantitative indicators of forecast quality, the absolute and mean forecast errors exponentially smoothed with a parameter of 0.4 are investigated. It was found that for alcohol, the smoothed absolute and mean forecast errors for the classical smoothing parameter in the no-ignition interval do not exceed 20 %. At the same time, for the out-of-limit case, the indicated forecast errors are, on average, an order of magnitude smaller. Similar ratios for forecast errors remain in paper, wood and textile ignition. However, for the transition zone corresponding to the time of material ignition, a sharp decrease in the current measure of chamber air state gain recurrence is observed. It was found that for this zone, the smoothed absolute forecast error for alcohol is about 2 % if the model parameter is selected from the classical set. If the model parameter is selected from the out-of-limit set, the forecast error is about 0.2 %. The results generally demonstrate significant advantages of using the zero-order Brown parametric model with out-of-limit model parameters for indoor fire forecasting

Keywords: fire forecasting, zero-order Brown model, out-of-limit set, ignition, recurrence measure

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1. Introduction

According to world statistics, 8 million fires occur annually, in which more than 90 thousand people die. Any fire occurs in the presence of combustible material, oxidizer and fire conditions [1]. Fires in ecosystems [2], at production sites [3, 4], as well as in premises of various facilities are the most dangerous [5]. At the same time, indoor fires (IF)

are the most frequent. The danger of such fires is associated with a significant threat to human life and health [6]. In addition, IF violate the integrity and stability of the facilities themselves [7], as well as the balance in the natural environment [8]. Large-scale fires lead to acid precipitation and aquifer pollution [9]. For example, according to the National Fire Protection Association, in 2019 in the United States, an IF was reported every 93 seconds, and death occurred every 3 hours. Property damage amounted to about $ 12.3 billion [10]. This demonstrates the ineffectiveness of existing measures and technologies, as well as the relevance of the general IF protection problem. One of the ways to solve this problem is short-term forecast (SF) of IF. SF allows timely detection of the onset of ignititon and preventing it from developing into fire. Due to the complexity and individuality of each IF, SF should be based on system representations of the interaction of fire hazards with indoor air as a single dynamic system and the use of modern methods of short-term forecasting of processes with random dynamics.

In this regard, the study of short-term fire forecast based on the state of indoor air as a single dynamic system and methods for forecasting processes with uncertain dynamics should be considered particularly relevant.

2. Literature review and problem statement

In [11], the results of a study of modern IF forecasting methods are presented. Such methods are based on models of formation of major hazards. At the same time, issues related to SF of fires in real premises remained unresolved. The known methods allow general description and calculation of the deterministic change in the air parameters in specific premises over time [12]. However, real conditions for IF occurrence are characterized by rather complex individual dynamics of current indoor air (IA) states. Therefore, SF of fires in various real premises based on the known methods is difficult to implement.

In the conditions of real IF, IA is a complex dynamic system with the properties of dissipative structures, state nonlinearity, and self-organization [13]. In such systems, the known methods do not allow identifying complex relationships between elements, since they are based on the principles of linearity, which are violated in real conditions. This leads to an erroneous assessment of IA dynamics, which does not allow the implementation of IF SF [14]. However, [15] notes that the nature of current IA dynamics is of paramount importance for IF SF. In such conditions, nonlinear dynamics methods for the analysis of various complex systems can be used for IF SF [16]. Quantitative methods of the nonlinear dynamics of various complex systems operating under nonstationary conditions are studied in [17]. Their application in geophysics based on fractal sets is considered in [18]. However, in [16–18], the IF SF methods based on IA state analysis in real conditions are not investigated. A number of papers present the results of experimental studies of early materials ignition and IF. So, [19] gives the results of experimental studies of the process of IF occurrence. A study of thermal radiation effect on heat release rate for various combustible materials is given in [20]. An experimental study of combustion modes of various combustible materials under the influence of an external heat flow was carried out in [21]. The work [22] is devoted to an in-depth study of the rate of heat release into the air during IF. It is noted that

IA state dynamics at the initial IF stage are complex and non-stationary. The work [23] is devoted to increasing the efficiency of IF detection based on the known methods. At the same time, the IF SF methods based on current IA state analysis are not considered or investigated [24]. In [25], it is proposed to use self-adjusting fire detection methods for non-stationary conditions. However, the proposed methods are limited to average values of individual IA parameters. Current IA state dynamics during a fire are neither taken into account and nor investigated. Due to the complex nature and unpredictability of real IA state dynamics, the research results presented in [26] are limited only to an adaptive threshold and fire detection probability. In [27], the dynamics of time autocorrelations and pair correlations of the IA state were investigated using the example of test fires in a model chamber. It is noted that current indicators of IA state parameters rather than their time correlations should be considered more important for early fire detection. Methods suitable for fire detection based on IA state parameters are discussed in [28]. However, these methods are valid only for stationary conditions and are based on average IA parameters. The time-frequency features of IA state dynamics are not taken into account, which does not allow using them for IF SF. Methods for early IF detection based on time and frequency changes in IA states are discussed in [29]. It is noted that the problem of time-frequency fire detection based on IA states remains unresolved. At the same time, the known methods are difficult to implement and unsuitable for IF SF. The method that takes into account non-stationarity of IA parameters during ignition is studied in [30]. However, this method is based on the application of the Fourier transform to stationary fragments of nonstationary IA state dynamics. In the case of IF, it is not possible to distinguish stationary fragments in the non-stationary state dynamics of dangerous IA parameters. In the above-mentioned works, IA during a fire is not considered as a single complex dynamic system, state dynamics of such a system were neither investigated nor forecasted. In [31], the results of experimental study of combustion rate dynamics of various materials in closed and ventilated premises are presented. However, there are no data on the features of IA state dynamics. The work [32] is devoted to studying the dynamics of gains of individual IA parameters. It is noted that the dynamics of such gains can be considered as an effective indicator of fire detection and IF SF. However, the research results are limited to traditional statistical gain parameters. It is noted in [27–32] that materials ignition is a source of violation of the initial dynamic equilibrium of IA states. It is found that IA state dynamics during ignition have a complex nonlinear and non-stationary character. Application of methods of time-frequency identification of nonlinear dynamic systems to identify the specified IA features during ignition is considered in [33, 34]. The short-term Fourier transform method of fire detection is considered in [35]. However, [33–35] note that the considered methods are rather complicated and cannot be used for IF SF. It is indicated that the state and state gain dynamics of IA as a complex dynamic system are important for early fire detection. Application of the time-frequency method to assess IA dynamics during ignition is considered in [36]. It is noted that the method is rather difficult to implement and lacks efficiency for IF SF. In [37], a method for operational IF forecasting in real conditions is proposed. The method is based on presenting IA as a complex dynamic system, the state of which is assessed by a vector of fire hazards. For IF

SF, it is proposed to use IA state gain recurrence in the zero-order Brown model. However, it is known that SF quality in the above model depends significantly on the value of the exponential smoothing parameter [38]. Moreover, in [39], accepted permissible limits for the indicated parameter are expanded. Such an extension of classical limits is commonly called out-of-limit. However, [37] lacks a study of IF SF based on the zero-order Brown model in the classical and out-of-limit cases.

It follows from the analysis that IA state dynamics during IF have a complex and nonlinear character, depending on specific real conditions determined by a number of unknown and time-varying factors. There are various methods of fire detection. However, existing methods are quite complex, have limited sensitivity, efficiency and scope. For this reason, using them for IF SF is problematic. Methods based on the nonlinear dynamics of current IA states are more acceptable [37]. Such forecasting methods should be based on IA state gain recurrence dynamics. At the same time, SF based on the zero-order Brown forecasting model is the most important in terms of IF forecasting [37]. Due to the parametric dependence of forecast, an important and unresolved part of the problem is to study IF SF based on the parametric zero-order Brown model.

3. The aim and objectives of the study

The aim of the work is to study short-term indoor fire forecast based on the zero-order Brown model for the current measure of IA state gain recurrence at different values of the exponential smoothing parameter.

To achieve the aim, the following objectives were set:

– to evaluate the possibility of parametrization of the zero-order Brown model when used for indoor fire forecasting based on the current air state gain recurrence measure;

– to investigate errors of air state gain recurrence forecast based on the zero-order Brown model at different parameter values using the example of test materials ignition in a laboratory chamber simulating a permeable room.

4. Materials and methods of the study

Alcohol, paper, wood and textiles, which are most typical for premises of various facilities, were studied as combustible materials. The choice of these materials is also due to the fact that they have different ignition rates. The study of short-term indoor fire forecast was carried out on the basis of time-discrete measurements of air state, characterized by a vector of fire hazards [32]. Temperature, smoke density and carbon monoxide concentration in the air of the laboratory chamber simulating a permeable room with natural ventilation during ignition of the studied combustible materials were investigated as fire hazards. Measurements were made at discrete times [32] i=0,1,2,...., 400, then with a 0.1 s interval. Ignition of combustible materials in the laboratory chamber was carried out approximately in the region of i=200 counts. The main fire hazards, determined by smoke density, temperature and carbon monoxide concentration of IA were measured [11]. These fire hazards were measured using the TGS2442 (Japan), DS18B20 (Germany) and MQ-2 (China) sensors. Each of the sensors was tested for compliance with the declared parameters before the study.

The research methods were based on the results of a systemic analysis of IF occurrence [14], taking into account the method of recurrence plots (RP) [40]. Following [14], the air in the chamber was considered as a certain complex dynamic system, the state of which was determined by the properties of combustible materials, the parameters of the laboratory chamber and the effect of various disturbing factors. It was taken into account that in real IF conditions, air states are usually unknown in advance and can change unpredictably over time. Therefore, the air state in the chamber was estimated based on real-time measurement information of IA hazards [41]. Based on the measurements of chamber air fire hazards, the vector of current gains of the IA state vector was determined. The current IA state vector gains were used to determine the current measure of their recurrence [42]. The determined current measure for the IA state vector gains was used in the zero-order Brown model for IF SF [37].

The study of IF SF errors based on air state gain recurrence using the zero-order Brown model with the value of the exponential smoothing parameter from the classical and out-of-limit regions was carried out using the example of real ignitions of combustible materials in the laboratory chamber simulating a permeable room. A quantitative assessment of SF quality was made by calculating the exponentially smoothed current absolute (MAE) and mean (ME) forecast errors for the smoothing parameter from the classical and out-of-limit regions. The data were recorded and processed on a PC with the Windows 10 system, as well as special data recording software and data processing software in the Mathcad 14 computing environment.

5. Results of the study of short-term fire forecast using the Brown model

5. 1. Assessment of the possibility of parametrization of the zero-order Brown model in fire forecasting

The general theoretical justification of the IF SF method on the basis of the current IA state gain recurrence measure and the zero-order Brown model based on the exponential smoothing procedure is presented in [37]. The current IA state gain recurrence measure in real conditions changes under the influence of many dangerous and interfering factors of materials ignition [43, 44]. In some cases, the combination of these factors can cause both an increase and a decrease in current IA state gain recurrence. These situations can also alternate. Obviously, under these conditions, IF SF should be adaptive to the current gain recurrence measure, which has random dynamics without obvious signs of trend and seasonality. Therefore, [37] proposes to use the known zero-order Brown model for IF SF, but for the current IA state gain recurrence measure. IF SF in accordance with the zero-order Brown model and current IA state gain recurrence measure is determined by the formula

$$P_i = hAs_i + (1-h)P_{i-1}, \qquad (1)$$

where P_i – forecast value at time i; h – smoothing parameter value; As_i – value of the current IA state gain recurrence measure at time i; P_{i-1} – forecast value at time i–1.

The choice of the smoothing parameter value in (1) usually satisfies the classical smoothing condition determined by the inequality $0<h<1$. Parametrization of the model (1) is widely used in forecasting economic systems with different

state dynamics [45]. Sequential application of the relation (1) determines IF SF P_i as the sum of all exponentially weighted current recurrence measures at time i and up to i. Following Brown, the variance $D[P_i]$ of the forecast (1) is determined as

$$D[P_i] = \frac{h\sigma^2}{2-h},\qquad(2)$$

where σ^2 – variance of the current IA state gain recurrence measure.

It follows from the expression (2) that with decreasing h, the forecast variance decreases. To increase the weight of the last values of the current gain recurrence measures, the parameter h should be increased. Converting the relation (1), IF SF in accordance with the zero-order Brown model and current IA state gain recurrence measure is presented as follows:

$$P_i = P_{i-1} + h\left(K_i - P_{i-1}\right).\qquad(3)$$

It follows from the expression (3) that the value $(K-P_{i-1})$ determines the current IF SF error. Following (1) or (2), exponential smoothing of the current IA state gain recurrence measure implements a version of the Brown self-learning model. Calculation of IF SF in this case is simple, implemented iteratively and requires minimum memory. The parameter h is important for the considered Brown model. This parameter characterizes the adaptability of IF SF (1) or (3). In the classical use case (1) and (3), the parameter h is selected in the range from 0 to 1. However, [43] proved that in the considered Brown model, instead of the classical limits of the parameter h from 0 to 1, this parameter should be selected within wider limits – from 0 to 2. It is shown that in forecasting a real transition economy, forecasts are the best when the parameter h is selected from the out-of-limit set from 1 to 2. The hypothesis was made that the out-of-limit set of the parameter h is the area of effective forecasting of non-stationary processes. This hypothesis was confirmed by a number of practical examples. It is noted that the final justification of this hypothesis requires broader theoretical and empirical research. Practically unexplored is the case of the out-of-limit set of the parameter h for the zero-order Brown model for IF forecasting [40]. Thus, the study of IF SF when the parameter h is selected from the out-of-limit set using the zero-order Brown model for the current IA state gain recurrence measures using the example of materials ignition in a laboratory chamber is important and relevant.

5. 2. Study of the error of fire forecast based on the zero-order Brown model

The object of the study was IF SF based on the zero-order Brown model for the current IA state vector gain recurrence measures. In this case, the choice of the parameter h corresponded to an extended set from 0 to 2. The subject of the study was the quantitative indicators of forecast quality for the model parameter h from the classical and out-of-limit sets. As quantitative indicators for the quality of forecast based on the current IA state vector gain recurrence measure [40], the dynamics of the current absolute and mean forecast errors exponentially smoothed with a parameter of 0.4 were investigated. As an illustration of the results, the figures below show the characteristic forecast MAE and ME dynamics for two values of the parameter h of the Brown model from the classical and out-of-limit sets, equal to 0.2 and 1.2, respectively.

For example, Fig. 1 illustrates the characteristic forecast MAE and ME dynamics for the specified values of the model parameter h for alcohol ignition in the laboratory chamber. Similar relationships for paper, wood and textile ignition are shown in Fig. 2–4, respectively.
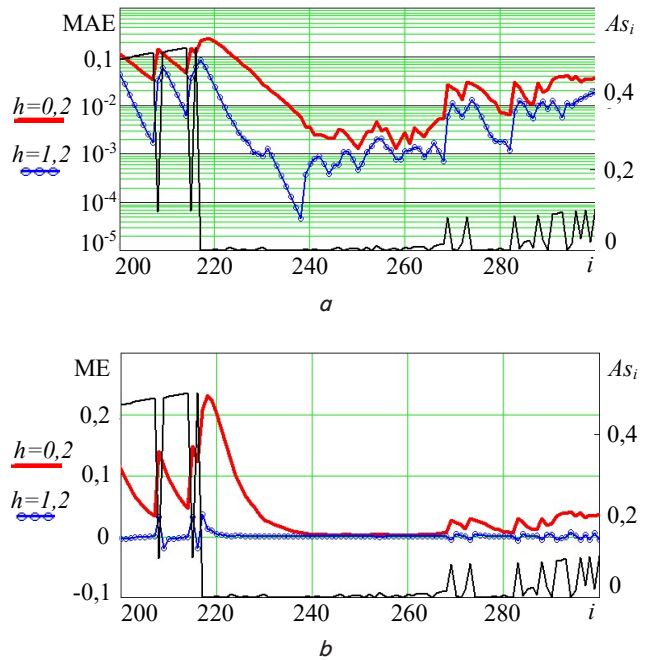

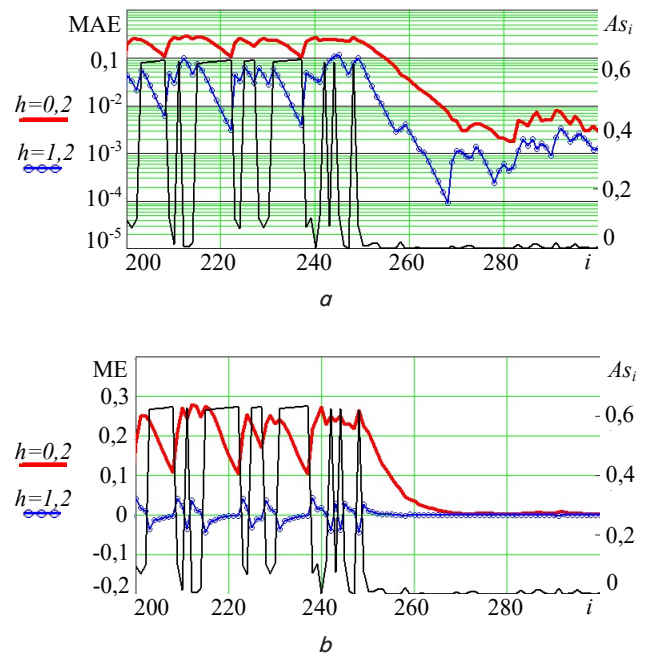Fig. 1. Forecast error dynamics for alcohol ignition:
a — MAE; b — ME

Fig. 2. Forecast error dynamics for paper ignition:
a — MAE; b — ME

Fig. 1–4 show in black the dynamics of the current chamber air state recurrence measure for the corresponding test materials.
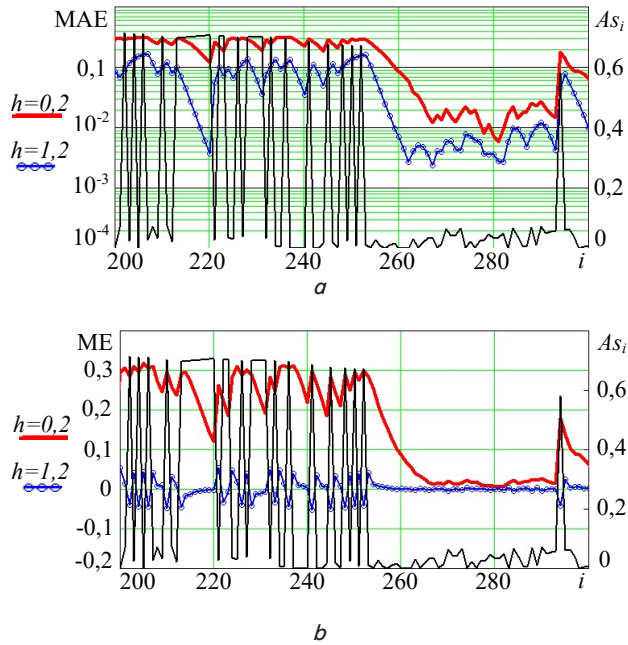
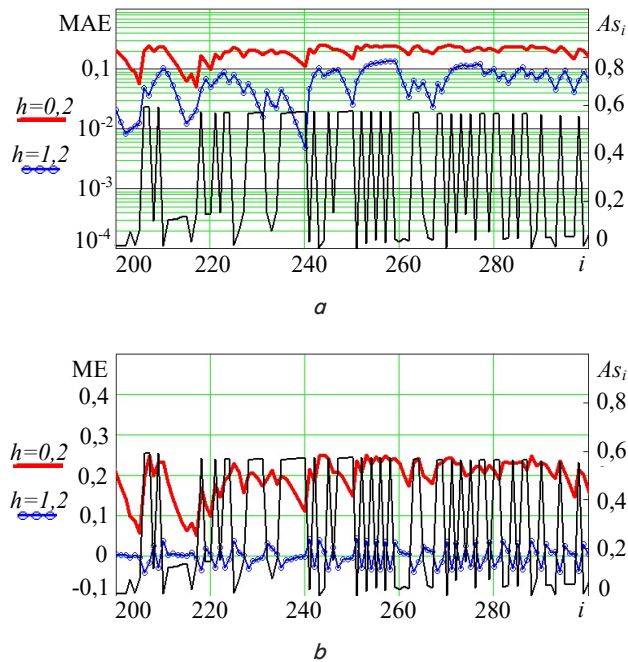Fig. 3. Forecast error dynamics for wood ignition:
a — MAE; b — ME

Fig. 4. Forecast error dynamics for textile ignition:
a — MAE; b — ME

6. Discussion of the results of the study of fire forecast error dynamics

The results of the study of forecast error dynamics for the ignition of various materials shown in Fig. 1–4 are explained by different capabilities of the zero-order Brown model to carry out IF SF when the smoothing parameter is selected from the classical and out-of-limit sets. Experimental data for MAE and ME dynamics generally confirm the hypothesis that the out-of-limit set for the smoothing parameter

of the Brown model makes it possible to efficiently forecast non-stationary current measures of IA state vector gain recurrence. The obtained quantitative indicators of forecast errors, determined by MAE and ME, demonstrate their difference for both the same and different combustible materials. The studied quantitative indicators of forecast errors for different materials of ignition in the laboratory chamber are about an order of magnitude lower for the out-of-limit set of the smoothing parameter compared to the classical set. So, the MAE and ME values for alcohol with the classical smoothing parameter provide a forecast error in the no-ignition interval not exceeding 20 %. In this case, the choice of the smoothing parameter from the out-of-limit set provides, on average, an order of magnitude lower forecast error in the specified interval. This is especially true for the time with a greater measure of current chamber air state gain recurrence. Similar patterns of quantitative indicators of forecast quality remain in paper, wood and textile ignition.

In the transition zone corresponding to the moment of materials ignition, the MAE value for alcohol corresponds to a forecast error of about 2 % for the smoothing parameter from the classical set and 0.2 % for the out-of-limit set. In addition, MAE dynamics in the transition zone indicate a higher forecast accuracy at the beginning of the transition zone for the out-of-limit Brown model parameter. In this case, the ME value is more than an order of magnitude lower than the parameter from the classical set. A similar situation is observed in the ignition of other materials. However, MAE and ME dynamics for textiles in the studied interval differ from other materials (Fig. 4). This is explained by the low ignition rate of textiles, which in the considered interval does not lead to a noticeable decrease in the measure of the current chamber air state gain recurrence. Thus, the experimental data presented in Fig. 1–4 generally show the advantages of using the zero-order Brown model with the smoothing parameter from the out-of-limit set for IF SF.

The limitations of this study include the fact that the results are based on experimental data of ignition of a limited number of combustible materials in a laboratory chamber. The analyzed quantitative indicators of IF SF quality will depend on laboratory chamber parameters, ignition source dimensions and the distance of the corresponding sensors from the source. Therefore, in real IF SF conditions, it is advisable to place IA hazard sensors in areas of maximum ignition probability. Such areas in facilities are usually known in advance. Traditionally, ceilings are considered to be effective areas for placing sensors.

Possible ways to further develop the study can be to expand the scope of experimental research to various types of premises and fire loads in them. In the course of extended experimental studies, it is necessary to clarify recommended values of the smoothing parameter from the out-of-limit set, as well as evaluate validity limits, restrictions and stability conditions of IF SF.

7. Conclusions

1. Possibilities of parameterization of the zero-order Brown model for indoor fire forecasting based on the current measure of air state gain recurrence were estimated. The parameterized Brown model depends on the smoothing parameter, which characterizes the forecast adaptability to the current indoor air state gain recurrence measure. It is

noted that the specified parameter should be selected from a set between 0 and 1 (classical set). However, it is known that instead of the classical set, the model parameter should be selected from the extended set between 0 and 2. It is also noted that the out-of-limit set of the smoothing parameter from 1 to 2 provides effective forecasting of non-stationary processes without trend and seasonality. The case of the out-of-limit set of the parameter for the zero-order Brown model for fire forecasting based on the current air state gain measure remained unexplored. Therefore, it is important to investigate the extended set for the Brown parameter model for short-term indoor air forecast based on the current air state gain recurrence measures.

2. Errors of fire forecast based on the parameterized zero-order Brown model in the case of the extended parameter set were investigated using the example of ignition of various combustible materials in a laboratory chamber simulating a permeable room. As quantitative indicators of forecast qual-

ity, the absolute and mean errors exponentially smoothed with a parameter of 0.4 are considered. It was found that for alcohol, the smoothed absolute and mean forecast errors for the classical smoothing parameter in the no-ignition interval do not exceed 20 %. At the same time, for the out-of-limit case, the indicated forecast errors are, on average, an order of magnitude smaller. Similar ratios for forecast errors remain in paper, wood and textile ignition. However, for the transition zone corresponding to the time of material ignition, a sharp decrease in the current measure of chamber air state gain recurrence is observed. It was found that for this zone, the smoothed absolute forecast error for alcohol is about 2 % if the model parameter is selected from the classical set. If the model parameter is selected from the out-of-limit set, the forecast error is about 0.2 %. Thus, the results generally demonstrate significant advantages of using the zero-order Brown parametric model with out-of-limit model parameters for short-term indoor fire forecast.

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