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CONSTRUCTION OF A METHOD FOR DETECTING ARBITRARY HAZARD POLLUTANTS IN THE ATMOSPHERIC AIR BASED ON THE STRUCTURAL FUNCTION OF THE CURRENT POLLUTANT CONCENTRATIONS

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This paper reports the construction of a method for calculating the structural function within a moving window of the fixed size, based on measuring the vector of current concentrations of arbitrary air pollutants. The use of a moving window makes it possible to reveal the current moments of the emergence of inhomogeneities in the polluted atmosphere. In this case, the time shift of the structural function reveals the corresponding time scale of this heterogeneity. It has been shown that, in contrast to the known method, the proposed method makes it possible to reveal the dynamics of the levels and scales of local inhomogeneities of the polluted air using only the current measurements of concentration for an arbitrary number of pollutants. It is noted that the method does not use information about the current meteorological conditions of the atmosphere and the features of urban infrastructure near a pollution control point. Therefore, the method is universal; it could be applied to arbitrary control points of atmospheric pollution across various territories of states. The efficiency of the proposed method was tested using the example of actual measurements of the concentrations of urban air pollutants involving formaldehyde, ammonia, and nitrogen dioxide. The reported results generally indicate the applicability of the proposed method. It has been experimentally established that the method makes it possible to identify, in real time, the areas of local inhomogeneities characteristic of hazardous air pollution associated with the absence of dispersion and accumulation of pollutants in the air. In addition, the method makes it possible to detect in real time both the levels and the scale of inhomogeneities in the polluted atmosphere. It has been experimentally established that before the occurrence of the tested reliable emergency in a polluted atmosphere, the level of local heterogeneity was 0.015 units at its time scale corresponding to 8 counts. Next, by the time of the emergency, the level of heterogeneity decreased to 0.0025 units at the time scale corresponding to 2 counts. It has been experimentally established that for this case the forecast time of the occurrence of an emergency was 4 counts or 24 hours

Keywords: air pollution, structural function, detection of hazardous pollution, pollution inhomogeneity scale

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1. Introduction

At present, there is a big enough global evidence base [1] on the impact of air pollution on the health of the population [2], and the deterioration of climate across the entire planet [3]. According to the World Health Organization, the main global threats to humans in 2019 were ambient air pollution (AAP) and climate change [4]. A report by the

Organization for Economic Cooperation and Development indicates that the AAP could cost the world USD 2.6 trillion per year by 2060, including hospital costs, medical bills, and reduced agricultural production. Moreover, by 2060, social security costs associated with premature deaths related to AAP could rise to USD 25 trillion [5]. AAP affect the life of society and even endanger the survival of humanity. Currently, about 9 million people die every year as a result of global AAP [6]. Typically, AAP consist of a mixture of gases and particles in harmful quantities that are released into the atmosphere as a result of natural or anthropogenic activity [7]. The additional hazard of AAP increases significantly under conditions of stagnant atmospheric phenomena. Today, due to the development of industrialization, the increased number of vehicles, and the burning of fossil fuels, air quality is deteriorating while its pollution is becoming more serious and dangerous. Dangerous air pollutants are SO_2, NO_2, CO_2, NO, CO, NO_x, $PM_{2.5}$, and PM_{10}, etc. At the same time, there are no currently known levels of AAP that would be safe for humans [4]. Consequently, it is now accepted to consider effective strategies to minimize the current AAP. The non-linear nature of the dose-response curves for most health indicators shows the danger of AAP at lower concentrations of pollutants than their maximum permissible concentrations (MPCs) [8]. Therefore, the protection of atmospheric air from AAP is becoming one of the main issues at the present stage of the safe development of civilization [9]. Timely identification of hazardous contaminants should be considered important in the implementation of the strategy for minimizing current AAP, both during the planned activities of enterprises and in the elimination of emergency situations (ES). Hence, the methods for detecting dangerous contaminated substances in real time are especially relevant.

2. Literature review and problem statement

Work [10] reports the results of a study aimed at identifying global trends related to the emergence of hazardous contaminants over the vast territories of different countries. To identify these trends, only open data are usually used [11], typically averaged over a sufficiently long period of time [12]. At the same time, the results of such studies are limited mainly to the data for the average annual concentrations of typical AAP [13]. In this case, the task to identify current dangerous AAP in real time is not resolved. However, this problem is especially relevant for the protection of the air and the operational control over AAP. The lack of solutions is associated with the complexity of the current processes of the dispersion and accumulation of AAP, which depend on a set of a priori unknown parameters. For this reason, there are no methods for detecting current hazardous AAPs based on non-traditional views of the AAP system as a whole within the conventional hazardous AAP detection toolkit. A detailed analysis of existing methods and models used to detect AAP is performed in work [14]. Based on this work, the known methods for detecting AAP can be divided into three main classes: potential methods [15], statistical methods [16], and numerical methods [17]. However, the known methods and models [15–17] are not universal and turn out to be rather complicated. In addition, their implementation requires a significant amount of a priori data, including information on the meteorological parameters of the state of the atmosphere. At the same time, some of the methods are not robust enough and are sensitive to the type and nature of the initial a priori data. Given the limitations noted above, the known methods do not allow detecting dangerous AAPs in real time for various territories. However, it is noted in [18] that the issue of detecting AAP in real time remains unresolved although it is of paramount importance for the implementation of various management strategies and preventive measures to protect the atmosphere from AAP. Work [13] focuses on solving the issue of processing large amounts of data; it proposes using Bayesian networks to tackle the problem. However, such networks turn out to be quite complicated to implement and require significant computing costs. Therefore, the method reported in [13] has limited capabilities for detecting AAP in real time. At the same time, the methods given in [13, 15–17] are more suitable for solving the task of identifying global AAPs and developing, on their basis, preventive measures over the long term, taking into consideration the peculiarities of the development of specific territories. Therefore, along with [13, 15–17], modern methods for AAP detecting have been constructed. Their difference from known methods is in representing the polluted atmosphere as a complex and nonlinear dynamic system. And the state of such a system is determined by many factors that are linked via an unknown relation that often changes over time. This makes it possible to use the modifications of known nonlinear dynamics methods for real-time detection of dangerous AAP conditions. So, for example, work [19] addresses the application of methods based on the state recurrent measures in complex dynamical systems. Among the modern techniques for identifying features in the dynamics of states of complex dynamical systems is the method of recurrent plots (RP) [20]. A method for identifying recurrent states in a gaseous medium based on the use of the correlation dimensionality of states is considered in [21]. However, this method turns out to be rather difficult to implement, and its accuracy depends essentially on a series of parameters that must be selected a priori. The identification of hazardous conditions of the polluted atmosphere in industrial cities based on the use of RP is considered in paper [22]. In this case, the calculation of RP is limited to considering only one of the coordinates of the multidimensional state AAP vector. The results from applying the RP method for the case of a 5-dimensional state vector of wind speeds in five regions of Nigeria were considered in [23]. However, the research is limited to considering the RP method only for the Euclidean metric. At the same time, a limitation of the method is the dependence of the result of calculating RP on the used recurrence limit, determined a priori. The solution to the general issue of eliminating artifacts in the RP method using the Euclidean metric is considered in [24]. The RP method application for the vector of measured states of the Earth's magnetosphere is considered in [25]. However, the results are limited to the maximum metric and the Chebyshev metric. The sensitivity of the RP method to the value of the selected limit is also noted. Work [26] tackles the application of the RP method for the recognition and classification of human motor activity. It is noted that the method demonstrates low reliability associated with the threshold uncertainty. To overcome the threshold uncertainty, it is proposed to calculate a distance matrix instead of RP, which does not depend on the threshold. Based on this matrix, it is possible to recognize and categorize movements using a neural network. However, the use of neural networks is associated with certain drawbacks and limitations. In this case, the efficiency of the method is low. The application of the RP method for revealing the features in the performance of bio-systems is considered in [27]. It is noted that the reliability of the RP method is significantly influenced by the measurement conditions, the value of the time delay, the dimensionality of nesting, as well as the value of the recurrence threshold. Work [28] reports the method for calculating RP under conditions of irregular measurements. However, the reported studies are limited to considering only a standard distance metric. General recommendations for overcoming the threshold uncertainty of RP methods are given in [29]. It is noted that there are general recommendations for fixing the threshold depending on the specific goal of a study. More specific recommendations are given in [30], which argues that the threshold value should be some function of the standard deviation in the measurement results. However, the type of the function is not specified.

The combination of a multilevel network approach and recurrent networks for identifying the features of the states' dynamics of multidimensional complex dynamic systems is considered in [31]. In this case, the research is limited to considering a multidimensional state vector within a space with a Euclidean metric. The correlation and structural methods for identifying the features of the multidimensional states' dynamics are not considered, nor reported. The peculiarities of modern RP methods and their applications are considered in [32]. Meanwhile, it is noted that the RP calculation can be performed in spaces with different types of metrics. However, the issues of the influence of the metric and the value of the recurrence threshold on the accuracy of RP mapping are not considered. Possible methods of identifying the features of the states' dynamics in complex systems based on principles other than RP, for example, correlation or structural, are not discussed, nor proposed. The results of using RP methods for detecting hazardous states of a gaseous environment in premises and their modifications are considered in [33–35]. In [33], the use of the RP method for the concentration of carbon monoxide in a gaseous environment during early fires in non-air-tight premises is considered. In this case, the results are limited to a one-dimensional space with standard and power-law distance metrics. Correlation or structural methods for detecting early fires are not considered. Possible ways to adapt the threshold when calculating RP in the case of early fire detection are considered in [34, 35]. In [35], it is noted that the threshold adaptation is a key procedure in identifying hazardous conditions based on RP. In this case, the correlation and structural principles of identifying dangerous states are not considered in [33–35]. In addition, the known RP methods are not operational and have a series of application limitations. In some cases, the identification of recurrent states based on distance does not provide the required display accuracy and is rather rough and ambiguous. Study [36] substantiates a method for real-time detection of recurrent states of a complex dynamic system in the form of a polluted atmosphere, which is based on the implementation of the correlation approach. The approach from [36] is based only on the current measurements of a state vector and does not require the determination of the threshold and the procedure for calculating the distance, traditionally used in the RP method. However, the method from [36] is limited to a correlation assessment of the general level of energy interaction of state vectors, taking into account their current averages and fluctuations. It is known that the correlation approach is valid only in the case of stationary processes. For the case of non-stationary processes, the correlation approach turns out to be rather rough, and not applicable for applications. The structural approach is not considered in this case although it is known that it is applied in the case of non-stationary processes. Work [37] reports a study into the fluctuations of states in the form of the signs of early detection of dangerous states of a gaseous medium. However, the reported results are limited to the analysis of the statistics of increments in the basic factors. The structural features of the state dynamics of fluctuations are not considered. General methods of time-frequency representation based on a short-term Fourier transform are considered in [38, 39]. The application of a short-term Fourier transform to the analysis of real observations is considered in [40]. At the same time, the methods from [38–40] turn out to be rather difficult to implement, and cannot be considered as constructive in identifying dangerous states in complex dynamic systems. Methods that implement a structural or time-frequency approach are not considered. Work [41] addresses the development of a time-frequency approach for the case of analyzing the dynamics of hazardous states of a gaseous medium. Meanwhile, the general complexity of the developed time-frequency approach is noted. An AAP detection method based on the radial velocity and delay of measured AAP concentrations is reported in [42]. However, the obtained results are limited to the consideration of discrete measurements of AAP concentrations over a sufficiently long time interval. In addition, this method does not allow detecting dangerous AAP based on the fluctuations in a concentration vector, which is the main informational attribute of their emergence [37]. That limits the ability to detect dangerous AAP conditions. Nevertheless, the structural features of fluctuations are not considered in [42].

It follows from our analysis that the known methods of global AAP analysis, as well as modern methods of RP, of the correlation and time-frequency analysis, have some limitations. These constraints prevent using these methods to detect dangerous AAP in real-time. Therefore, an important and unsolved part of the problem is the construction of a method for detecting various hazardous AAPs in real-time based on a structured approach that employs the measurements of the current values of the AAP concentration at an arbitrary control point only.

3. The aim and objectives of the study

The study aims to devise a method for detecting arbitrary hazardous air pollution in real-time based on a structural function determined from the current concentrations of a set of pollutants.

To achieve the aim, the following tasks were set:

– to construct a method for calculating a structural function in real time for an arbitrary set of current concentrations of air pollutants;

– to test the efficiency of the proposed method on the example of real concentrations of urban atmosphere pollution by typical harmful gas pollutants.

4. Construction of a method to calculate the structural function in real time

Typically, AAP concentrations are measured at discrete times i. In this case, the results of measurements at discrete times i over an assigned time interval represent the sequences of m-dimensional vectors Z_i. The size of such a vector would be determined by the amount of AAP whose concentrations are measured at the assigned control point [43]. In this case, the m-dimensional vectors Z_i of the AAP concentrations measured at discrete time points, and considered over the assigned observation interval, would represent, in a general case, the time realizations of the corresponding non-stationary discrete vector m-dimensional random process. This process would describe the non-stationary dynamics of the states of the polluted atmosphere by the assigned set of AAP at a control point. Given the non-stationary nature of this process, the analysis of its characteristics is not possible based on the correlation approach. It is known that the correlation approach is applicable only in the case of stationary processes and assumes the possibility of determining and the existence of a fixed mean value over the observation interval.

First, the correlation approach allows evaluating the quantitative characteristics of only a specifically known type of stationary process. Second, it makes it impossible to answer the question about process continuity. Classic illustrations of such two restrictions are, for example, two pairs of processes with the same covariance functions, such as Poisson and Wiener, in which the first is discrete, and the second is continuous. Third, if the covariance functions are determined with an error, for example, as a result of averaging and centering, then the result is significantly distorted. This is due to that the mathematical expectation is estimated through the arithmetic mean, which in non-stationary conditions is calculated with a shifting error. Fourth, the covariance functions do not contain information about the dynamic characteristics of processes and are not intended to study the behavior of the dynamics of system states. Moreover, they are only the numerical estimates of the statistical correlations between the sections of a stationary random process; the current AAP concentrations are not considered to be such [44]. When practically identifying the dangerous AAPs based on their representation in the form of a complex dynamic system, there is usually no data on the factors disturbing the system. Therefore, the only initial information for detecting AAP is the response of such a complex system in the form of the implementation of some non-stationary random process determined by the current AAP concentrations at a control point. For the case of discrete time, evolutionary changes in the polluted atmosphere would be determined by a random non-stationary time sequence of the m-dimensional Z_i vectors. An important class of dynamic stochastic processes reflecting evolutionary changes in complex systems, following [45], are the processes with stationary increments. Random processes of this type belong to the class of non-stationary random processes in terms of mathematical expectation. It is known that the main characteristic of such processes is the structural function, which is invariant to the dynamics of the mean value of the process and is functionally related to its spectral properties [46].

A method of structural analysis is based on the a priori assumption that for the studied nonlinear dynamic systems there is an adequate mathematical model within a certain class of nonstationary functions. Regarding a random non-stationary time sequence of the m-dimensional Z_i vectors, whose average value changes over time, we shall consider a sequence in the following form:

$$Z_{i,\tau} = Z_i - Z_{i-\tau},\quad Z_i \in \Omega^m, Z_{i-\tau} \in \Omega^m,\quad i = 0,1,2,\ldots,N-1, \tag{1}$$

where $Z_{i,\tau}$ is the m-dimensional vector of the difference between the measurement vector Z_i and the measurement vector $Z_{i-\tau}$ at moment $i-\tau$, for the discrete values $\tau=0,1,2,\ldots,M-1$, under the condition $M<<N$; N is the total number of the m-dimensional Z_i vectors, measured over the observed interval, and Ω^m is the set of all measured vectors.

At small τ values, slow changes in the sequence of vectors Z_i would insignificantly affect the values of difference vector (1). This means that as a result of suppression of the component with very large periods, the sequence of the m-dimensional vectors of increments (1) would be stationary. Moreover, if $Z_{i\tau}$ turns out to be a random stationary sequence, then the original sequence of vectors Z_i is usually termed a random sequence with stationary increments.

Taking into consideration transformations (1), the structural function for the sequence of m-dimensional Z_i vectors of AAP concentrations would be determined by the function $C(\tau)$ of the discrete argument

$$C(\tau) = E_i\left\{\left|Z_{i,\tau}\right|^2\right\}, \tag{2}$$

where $E_i\{*\}$ denotes the discrete operator for calculating the mathematical expectation for a random sequence of the m-dimensional vectors, and $|*|$ defines the operator for calculating the modulus for the corresponding vector.

Structural function (2) reflects the presence and absence of oscillating components in the investigated random sequence of the m-dimensional Z_i vectors. Information on the presence of oscillating components can be used to detect the dispersion of air pollution [46]. In this case, the information about their absence could be used to identify the absence of dispersion or the accumulation of air pollution. In a general case, the structural analysis (2) of nonstationary random processes in a number of cases leads to more stable characteristics as compared with the correlation analysis [46]. Moreover, the parameters of the structural functions have the properties of invariance with respect to some forms of non-stationarity. In addition, the structural function (2) includes correlation characteristics and, for this reason, can be considered a result of a more general method of correlation processing of random processes. At the same time, the practical construction of a structural function is more reliable than the correlation function, since it is not affected by errors in determining the average value of the process.

It is known that an arbitrary random sequence Z_i would be a sequence with stationary first increments (1) only if its average value is the linear function of time [45]. Therefore, for small discrete time intervals τ, the capabilities of the structural approach to identifying dangerous real AAPs are significantly expanded in comparison with the correlation approach [37]. Following [45], an important property of structural function (2) is that it characterizes the intensity of those fluctuations Z_i whose periods are less than or comparable to the value τ of the delay. This means that slow, in comparison with the value of τ, changes in Z_i do not affect the difference (1) and therefore do not contribute to (2). Thus, the correlation function equally takes into consideration fluctuations of any scale. It is the use of the structural rather than the correlation function that turns out to be physically justified when large-scale fluctuations in pollution do not affect the detection of hazardous AAPs. This does not mean the absence of such fluctuations at all. Their share in the resulting fluctuations may even be large but, for the considered scale of the process of identifying dangerous AAPs, they can be considered insignificant.

Considering the specificity of measurements of the m-dimensional Z_i vectors, the developed method for detecting dangerous AAPs in real-time based on the structural function (2), will be determined, for vectors Z_i

$$C1(i,k,\tau)=\text{if}\left[i<(k+\tau),0,\frac{1}{k+1}\sum_{j=0}^{k}\left|Z_{i-j,\tau}\right|^{2}\right], \qquad (3)$$

where $C1$ (i, k, τ) is the structural function of the m-dimensional Z_i vectors, determined in the averaging window of the size of k counts for a fixed scale τ in the current discrete time of their measurement.

Structural function (3), in contrast to (2), depends not only on the scale τ of the region of fluctuations of the m-dimensional Z_i AAP vectors but also on the averaging window k, as well as the current measurement time. This means that method (3) allows detecting dangerous AAPs in real time based on the structural function for the m-dimensional Z_i AAP vectors, averaged in a window of the predefined size, for the fixed values of the time scales of the fluctuation region. In this case, a dangerous AAP would occur for such time scales for which function (3) is close to zero – the region of no fluctuations or the accumulation of air pollution.

The limitations of method (3) relate to that for the first $k+\tau$ discrete measurements, structural function (3) is not calculated and, following (3), is identically equal to zero. However, this situation can be corrected by replacing zero in expression (3) with a value that is different from zero. In this case, during the first $k+\tau$ discrete measurements of the m-dimensional Z_i vectors, a corresponding accumulation of data is performed for the subsequent implementation of method (3).

5. Testing the efficiency of the proposed method using the example of actual concentrations of atmospheric pollution

The efficiency of the developed method (3) was tested on the example of actual AAP concentrations. Typical gaseous AAPs from vehicles [47], fires [48], and accidents at high-risk facilities [49] were considered as the main pollutants. The concentrations of gaseous pollutants were measured at a specific point in the city. The close association of AAP with the greenhouse effect, acid rains [50], and the poisoning of aquifers [51] were considered. Therefore, formaldehyde (CH_2O), ammonia (NH_3), and nitrogen dioxide (NO_2) were chosen as the measured components of the AAP Z_i vector. The experimental measurement procedure and the characteristics of the equipment are given in [52].

Fig. 1 shows the current values of function (3), calculated for Z_i vectors measured at a predefined control point during the entire observation interval, from January to October 2018.

The specified function (3) corresponds to k=4 and the fluctuation scale τ=8, which is equivalent to 2 days. The measurement interval from 480 counts to 608 counts, which corresponded to the month of May, was chosen as a test method for verifying our method. The right-hand part of Fig. 1 shows the excess of the measured concentrations (C/MPC) of NO_2 and CH_2O over the corresponding maximum one-time permissible concentrations (MPC). Fig. 2 shows the AAP dependences of the structural function (3) on the current count only for the test interval of monitoring the pollutants CH_2O and NO_2 for the case k=4 and for various scales of fluctuations τ=8, τ=2. An actual emergency associated with massive disruption to the population life activities corresponded to count 508; it is denoted as a dangerous AAP in Fig. 2. The structural function (3) in the AAP dependence on the current count i and the scale of fluctuations τ for the case of the assigned parameter k=4 for a test interval in the form of the corresponding sections of the constant AAP level is shown in Fig. 3.

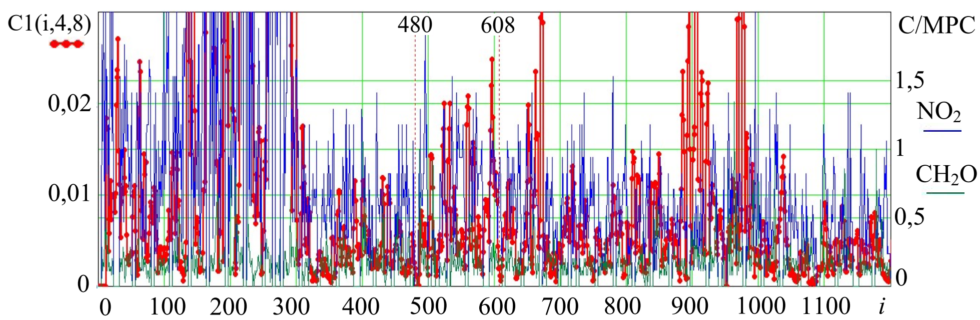

Fig. 1. Dependence of structural function (3) on the current count for the entire AAP control interval of CH_2O and NO_2

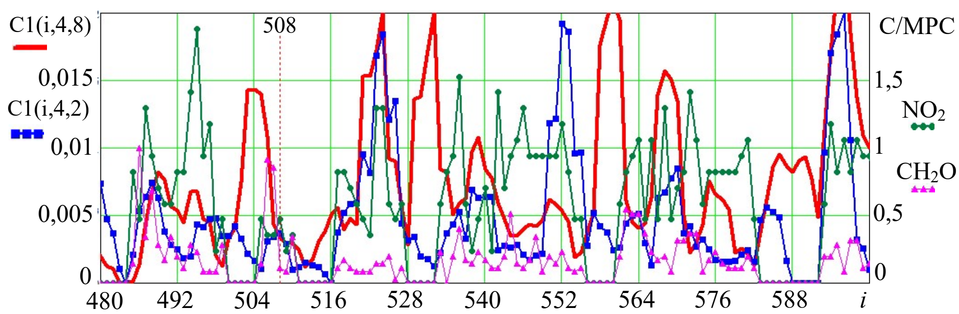

Fig. 2. Dependence of structural function (3) on the current count for the test interval of AAP control

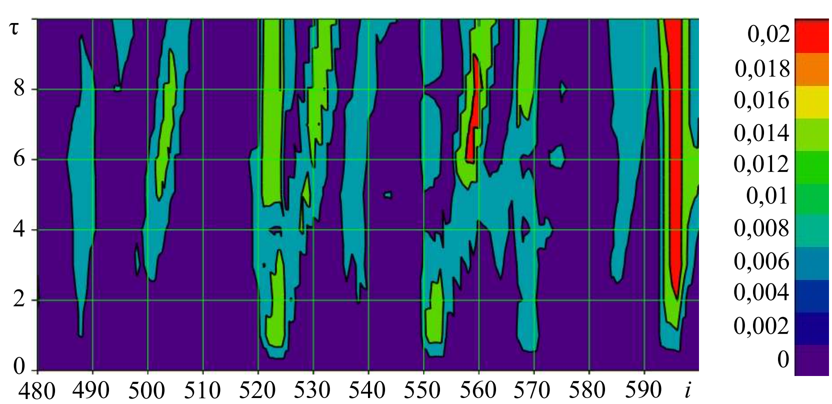

Fig. 3. Structural function (3) depending on the current count i and the scale of heterogeneity τ for the test interval of AAP control

With the aim of a more detailed analysis of the local AAP inhomogeneities at the time of the above emergency, similar AAP dependences for the interval limited to 500 and 512 counts are shown in Fig. 4.

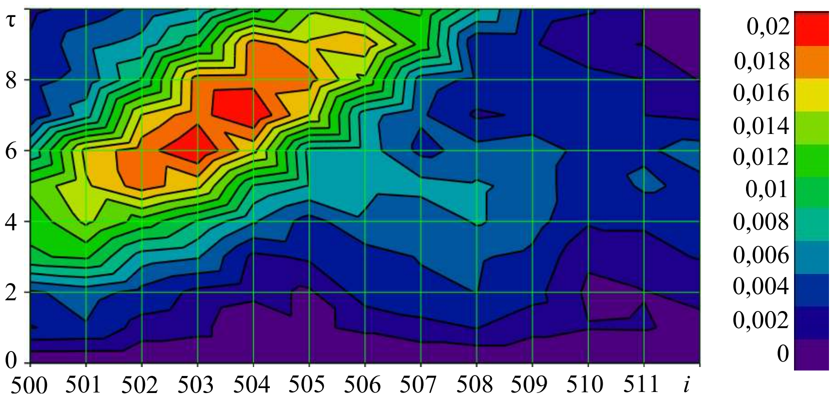

Fig. 4. Structural function (3) depending on the current count i and the inhomogeneity (fluctuation) scale τ for the test interval of AAP control linked to an emergency

Our verification of the proposed method in general has shown the possibility of the real-time detection of the areas and scales of local homogeneities and heterogeneities of pollution based only on the current measurements of the concentrations of an arbitrary set of harmful substances. This means that, based on the proposed method and the vector of current measurements of AAP concentrations, it is possible to identify hazardous and safe AAP inhomogeneities, as well as their areas and scales at arbitrary control points.

6. Discussion of results of the experimental testing of the proposed method

The reported results, illustrated in Fig. 1, 2 for different intervals of experimental measurements, are explained by the fact that the components of the vector of the current concentrations of gaseous AAP at the considered control point are the random non-stationary sequences. The structure and nature of these random sequences depend on many factors of the probabilistic nature, which are difficult to consider, to take into account in practice, or in mathematical models. Illustrations of the dependences of structural function (3) for the non-stationary measurement data of an AAP vector in a moving window, 4 count-wide (daily averaging), and two inhomogeneity scales, 2 counts long and 8 counts in Fig. 2, are explained by the fact that the AAP experimental environment is random and locally heterogeneous over time. At the same time, there are areas of the absence of local AAP heterogeneity, which are the local areas of pollution accumulation and the harbingers of the occurrence of possible dangerous AAPs.

The structural AAP features over a test interval that includes the moment of the occurrence of a reliable emergency (count 508) at a control point (Fig. 2) are explained by the fact that at the moment of count 504 preceding the moment of the emergency, the local heterogeneity of 0.015 units prevailed. The indicated heterogeneity showed the AAP dispersion. The time scale of this inhomogeneity was around 8 counts. The dispersion properties of the atmosphere at the time of count 508 decreased to the level of 0.0025 units, and a scale of 2 counts. This means that at the moment of count 508, the accumulation of the pollutants occurred at the control point, which led to the emergence of an emergency. The presence of inhomogeneities of various levels and time scales over an AAP monitoring interval indicates the presence of eddies. For the considered case, the inhomogeneity in the atmospheric air at the level of 0.015 units is 42.8 % and 17.6 % relative to the maximum one-time MPC, respectively, for formaldehyde and nitrogen dioxide. In this case, the heterogeneity at the level of 0.0025 units is 7.1 % and 2.9 %, respectively, for the above pollutants. This explains the fact that AAP irregularities at the moment of count 504 would have a greater effect on formaldehyde dispersion. However, in subsequent moments, this effect decreases, and the opposite effect of the accumulation of formaldehyde concentration occurs, which is confirmed by the experimental data at the time of count 508 in Fig. 2. At the same time, the level of the concentration of formaldehyde in the atmosphere almost reaches the value of the maximum one-time MPC (Fig. 2). The experimentally obtained levels of AAP inhomogeneity shown in Fig. 3 and Fig. 4 are explained by the complex and random structure of current local inhomogeneities, which are characterized by different time scales. Moreover, in Fig. 3, 4, there are areas in which the level of inhomogeneity is close to zero (the areas of purple and blue). The level of inhomogeneities in these areas is less than 0.002 units. Such areas are primarily characteristic of hazardous AAPs associated with the lack of dispersion and accumulation of pollutants by the atmosphere. A special feature of the proposed method is that measuring only the current concentration of AAP makes it possible to reconstruct in real time the levels and time scales of AAP inhomogeneities. At the same time, the level of heterogeneity and its time scale serves as the classification indicators for the detection of dangerous AAPs associated with the absence of dispersion and their accumulation in the atmospheric air. The data acquired indicate that the high-level AAP heterogeneities always precede the low-level heterogeneities associated with the occurrence of a dangerous AAP. This means that it is possible, based on the identification of high-level discontinuities, to predict dangerous AAPs in real time to prevent their occurrence. The reported results generally indicate the efficiency of the proposed method for detecting hazardous AAPs for the assigned set of current concentrations of pollutants in real time.

The limitations of the current study relate to that the results of the experimental verification of the efficiency of the method were performed for a limited number of pollutants of actual atmospheric air at the specified control point in a specific territory. Therefore, our results are partial. In this regard, a broader validation of the method is required, taking into consideration other hazardous AAP to humans and the environment. Thus, overcoming the noted restrictions can be considered a potential advancement of this study.

7. Conclusions

1. A method for calculating a structural function in a moving window of the fixed size has been devised for various

scales of temporal inhomogeneity, based on measuring a vector of the concentration of arbitrary air pollutants. It is shown that the proposed method makes it possible, in contrast to the known method, to reveal the features in the dynamics of the levels and scales of local inhomogeneities of polluted atmospheric air on the basis of current measurements of the concentration for an arbitrary number of pollutants only. It has been established that the high levels of heterogeneity could be used to predict hazardous air pollution, while the low levels of heterogeneity to identify them. It is shown that the method is universal since it is based on the current measurements of the vector of concentrations for an arbitrary number and type of air pollutants at a control point. Therefore, the method could be applied to arbitrary control points of atmospheric pollution in different territories of different states. It has been found that the method does not use information about the meteorological state of the atmosphere and about the features in the infrastructure surrounding the control point.

2. The efficiency of the proposed method was tested on the example of actual measurements of the concentrations of urban air pollutants with harmful substances in the form of formaldehyde, ammonia, and nitrogen dioxide. When standardizing the current concentrations, the maximum one-time MPC for the specified pollutants was considered. The results obtained confirm in general the efficiency of the proposed method. It has been experimentally established that the proposed method makes it possible to identify in real time the areas of the absence of local inhomogeneities, characteristic of the occurrence of hazardous air pollution associated with the absence of dispersion and accumulation of pollutants in the atmosphere. It was found that the proposed method makes it possible to detect in real time the levels and scales of inhomogeneities in the polluted atmosphere. Since high levels of heterogeneity always precede the occurrence of hazardous events, it is possible to predict hazardous air pollution in real time in order to prevent it. It has been experimentally established that before the occurrence of a test emergency in a polluted atmosphere the level of local heterogeneity was 0.015 units with a time scale of 8 counts (dispersion of pollutants). Then, by the time of the emergency, the level of heterogeneity dropped significantly. The level of local heterogeneity was 0.0025 units at a time scale of 2 counts. For a given case, it was found that the forecast time of the test emergency was 4 counts or 24 hours.

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