This paper has substantiated a modified method that, within the framework of the adaptive zero-order Brown's model, provides for increased accuracy in predicting processes with unknown dynamics masked by the noise of various levels. The forecasting method modification essentially involves an adaptive technique for determining the weight of the correction of the previous forecast, taking into consideration the recurrent state of the predicted process in time. To investigate the accuracy of the forecasting method, a test model of the process dynamics was determined in the form of a rectangular pulse with unit amplitude. In addition, a model of additive masking noise was defined in the form of a discrete Gaussian process with a zero mean and a variable value of the mean square deviation. Based on determining the exponentially smoothed values of current absolute forecasting errors, the dynamics of forecast accuracy were examined for the modified and self-adjusting methods. It was found that for the mean quadratic deviation of the masking noise equal to 0.9, the smoothed absolute prediction error for the modified method does not exceed 23 %; for the self-adjusting method – 42 %. This means that the prediction accuracy for the modified method is about twice as high. In the case of an average square deviation of masking noise of 0.1, the smoothed absolute prediction error for the modified and self-adjusting methods is approximately the same and does not exceed 10 %. That means that at a low level of masking noise, both prediction methods provide approximately the same accuracy. However, with an increase in the level of masking noise, the self-adjusting method significantly loses the accuracy of the forecast to the proposed modified method

Keywords: modified forecasting method, unknown dynamics, masking noise, Brown's model, forecasting errors

MODIFYING THE METHOD FOR FORECASTING HAZARDOUS PROCESSES WITH UNKNOWN DYNAMICS IN THE PRESENCE OF NOISE

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1. Introduction

Forecasting the state of complex objects in various fields [1] operating in unstable environments (UE) is the basis for solving the common problem of improving the efficiency of management of such objects [2]. The most important, from the point of view of civil protection, are dangerous objects [3] operating in UE [4]. These include

hazardous events in ecosystems [5] and socio-economic systems [6, 7]. The most dangerous, in this case, are fires in the premises (FP) [8]. This is due to the mass nature of such fires and their significant damage, both to human life and to the objects themselves [9], as well as to the environment [10, 11]. Therefore, forecasting the dynamics of the state of UE should be considered as one of the constructive approaches to ensuring the stability of objects [12]. The use of predictive technologies has made it possible to move from reactive to proactive control of objects. Such management is based on short-term forecasts (STF) of unknown dynamics (UD). However, the application of predictive technologies for objects characterized by UE turned out to be quite problematic. This is explained by the non-stationary and UD of predicted hazardous processes (HP), masked by noise (MN). To describe the HP, a mathematical apparatus based on the application of systems of differential equations and the general theory of the state space is used [13]. Existing models make it possible to describe the average dynamics of HP forecasting, characteristic of a limited number of objects and UE. However, these tools turned out to be poorly adapted to solve the tasks of STF and operational management in UE. At the same time, decisions on the operational management of non-stationary complex objects are often reactive in nature and are aimed at compensating for the already occurred emergency deviation of the dynamics of HP [14]. Such an approach inevitably reduces the effectiveness of emergency management and requires a transition to proactive management, which provides a proactive response to a possible set of non-stationary conditions that arise in UE. In this regard, the technology of HP STF with non-stationary and UD, MN, should be considered as an urgent issue.

2. Literature review and problem statement

Work [15] investigates traditional models of the dynamics of processes in UE in the form of deterministic differential equations. However, such models do not meet the requirements of operational proactive management. This is explained by the fact that real HPs contain complex jump-like and non-periodic components characteristic of dynamic chaos and non-stationary MN. As a result, conventional methods based on such models do not allow the formation of effective predictive solutions. The transition to more adequate models that meet the requirements of proactive HP management requires the development and application of qualitatively new technologies or modified STF methods based on modern mathematical and information technologies. In [16], the STF of the state of non-stationary HP based on artificial intelligence or data mining technologies is considered [17]. However, these methods turn out to be quite complex and do not meet the requirements of HP STF with UD. The results of modern system analysis and HP STF under uncertainty using stochastic models are tackled in [18]. The review of the cited work reveals that in the tasks of CP UD of the state and management of objects, there is a tendency to use modern data analysis theory, artificial intelligence technologies, and cognitive computing. However, the use of these technologies for the implementation of HP STF with UD in order to implement proactive management of complex objects turns out to be problematic. This is explained by the non-stationary and unknown dynamics of real environments [19]. Therefore, the problem of CP UD HP in order to

implement proactive management in unstable environments does not have a complete solution. It is known that adaptive methods and models provide the best results for CP HP with UD in noise. One of the widely used STF methods for this is the adaptive zero-order Brown's method (ZOBM) [20]. The main advantage of ZOBM is the ability to adapt STF to new observational data. In this case, the ability to adapt STF for ZOBM is determined by the parameter h, which acts as a corrective weight for current forecast errors. Paper [21] discusses the application of ZOBM to predict stationary processes. The study of the use of ZOBM for forecasting evolutionary processes is reported in [22]. The results obtained confirm the versatility of ZOBM for predicting various processes. In this case, the studies are limited mainly to a fixed value of the parameter h from the classical set between 0 and 1. However, there are currently many different ways to select this parameter. For example, in [23], the parameter h is offered to be selected subject to condition $0.1 < h < 0.3$. However, there is no justification for this recommendation. In [24], it is stated that for the particular dynamics of HP, there is a specific parameter value. The selection of such a value for the parameter h shall be based on the objectives of STF. For example, in [25], for STF of the dynamics of processes of an evolutionary nature, it is recommended to choose the parameter h subject to condition $0 < h < 1$, and, for processes with chaotic dynamics, $1 < h < 2$. It is noted that for each type of dynamics of the predicted HP there is the best value h to be determined. In [26], the parameter h is proposed to be selected experimentally for each specific predicted HP. However, this approach is not operational and is not suitable for forecasting HP. There is also a known approach [27], based on the choice of $h = 2/(k+1)$, where k is the number of steps included in the interval of smoothing the dynamics of HP. In this case, k is determined empirically, and the dynamics of HP is limited only by a random constant. The method of rapid identification of dangerous HP states based on the correlation approach is considered in [28]. However, the method is limited to a class of stationary processes. In addition, the issues of application of the method for the STF of HP taking into consideration UD are not considered. Paper [29] proposes an original modification of ZOBM for the HP STF with complex and UD [29]. In this case, the modification is based on the choice of the parameter h based on determining the Hearst indicator for the implementation of the predicted process. However, the main limitation of such a modification is the implementation complexity of the method, as well as the need for extended segments of stationarity. In addition, predicted processes must have special properties that are not usually present for real processes. In [30], it is proposed to modify ZOBM for HP STF based on the theory of functions of complex variables. A significant advantage of this modification is the lack of a priori information about the dynamics of HP. However, the method turns out to be difficult to implement and very sensitive to errors in the selection of initial values for the smoothing coefficient. These disadvantages, despite the existing advantages, limit the use of this method for HP STF with UD, MN of various levels. In our opinion, STF methods based on the results of the theory of nonlinear dynamics of complex systems are more constructive. A review of modern methods of quantitative analysis of the nonlinear dynamics of systems is presented in [31]. In [32], a method for rapid detection of atmospheric pollution based on the calculation of recurrent plots and measures of recurrent states (RS) of atmospheric pollution is proposed. The main limitation of the method is

the dependence of recurrence plots on the specified threshold distance, which determines the permissible degree of proximity of the analyzed states. The method of calculating recurrence plots with a self-adjusting threshold is considered in [33]. However, in [31–33], the methods of HP STF with UD against the background of the noise of various levels are not considered. Methods of HP STF with UD, MN, are considered in [34]. However, these methods are limited to the class of stationary models of HP dynamics. The method of estimating the non-stationary dynamics of HP is proposed in [35]. However, a given method is based on the interval Fourier transform to stationary fragments of the non-stationary dynamics of HP. At the same time, it is not possible to isolate stationary fragments in the case of UD. Methods of frequency-time identification of nonlinear systems are considered in works [36, 37]. However, the methods considered are complex and do not allow them to be used for HP STF with UD, MN. Paper [38] proposes an original method of frequency-time representation for identifying the dynamics of hazardous states of the gas environment during fires. However, this method turns out to be quite complex, which limits its application to HP STF. Therefore, study [39] proposes a modification of ZOBM for the STF of the current measure of recurrent increments of the HP state. Unlike [38], a given method has sufficient efficiency of the HP STF with UD, MN. However, the quality of STF significantly depends on the consistency of ZOBM smoothing parameter with the current dynamics of HP [40]. Similar limitations are characteristic of another method of HP STF based on ZOBM, proposed in [41]. Paper [42] considers a method for the rapid identification of hazardous air pollution conditions. The method is based on an analysis of the current RS measure for UD pollution. Methods of HP STF with UD, MN of various levels are not considered. This is due to the different purposes of the methods. To identify dangerous air pollution, in [43], it is proposed to use the uncertainty function for pollution. However, the STF method with UD is not considered in works [42, 43]. In [44], the accuracy of HP STF based on ZOBM is investigated. However, the study of the accuracy of HP STF is limited to fixed values of the smoothing parameter. Modification of ZOBM for the HP STF of UD processes is not considered. Study [44] offers an interesting version of the modification of ZOBM, which is self-adjusting based on observations, for the STF of the dynamics of irreversible HP and phenomena. However, the quality control of this method is limited to experimental data on the state of the gaseous medium in the laboratory chamber. Due to the uncertainty of the true dynamics of the state of the gaseous medium in the chamber, the assessment of the accuracy of STF given in [44] cannot be recognized as objective for assessing the quality of the method. For an objective assessment of the accuracy of STF methods, it is necessary to use test models of the dynamics of HP with the predefined level of observation noise. Thus, the unsolved part of the general problem under consideration is a modification of the method of forecasting HP with UD in the presence of noise, which provides an increase in the accuracy of STF under these conditions.

3. The aim and objectives of the study

The aim of this work is to modify the method of forecasting hazardous processes with unknown and non-stationary dynamics, masked by the noise of various levels, providing increased forecast accuracy within the framework of the adaptive zero-order Brown's model.

To accomplish the aim, the following tasks have been set:
– to substantiate within the framework of the adaptive zero-order Brown's model a modified method for predicting dangerous processes with unknown and non-stationary dynamics, masked by the noise of various levels, providing increased accuracy of the forecast;
– to determine a test model of the dynamics of the predicted process, as well as an additive noise model with a variable level to study the accuracy of the forecast;
– to investigate the accuracy of the forecast for the modified method on the example of the test dynamics of the process, masked by the noise of different levels.

4. The study materials and methods

The object of this study is ZOBM for HP STF with random dynamics, MN. The subject of this study is the modification of the adaptive ZOBM for forecasting HP with non-stationary and UD, MN of various levels, increased accuracy of STF. Usually, the accuracy of various methods of STF is assessed on the test dynamics of HP STF at different noise levels [20, 45]. As the universal and characteristic dynamics, the test dynamics in the form of a rectangular pulse with variable time parameters of its occurrence were chosen. As a test model of noise, the Gaussian process with zero mean and variable standard deviation (SD) was considered. To do this, we used the built-in special function in the Mathcad 14 programming environment (USA). The study was limited to investigating the additive effects of noise on the test dynamics of the predicted HP. The accuracy of the STF of the test dynamics of HP, MN with various SD, was determined by exponentially smoothed values of the current absolute errors of the STF. Exponential error smoothing was carried out in the current time with a window width determined by 80 counts. For the purpose of comparison, the smoothed values of the current absolute errors of STF were determined for the proposed modified method and the self-adjusting ZOBM [44].

5. Modifying the method of forecasting processes with unknown dynamics masked by noise

5. 1. Substantiation of the modified method for predicting processes with unknown dynamics masked by noise

The self-adjusting ZOBM, described in detail in [44], makes it possible to predict HP with UD, MN. However, a given method has the disadvantage associated with a decrease in the accuracy of UD STF with an increase in the level of MN. This is explained by the fact that the method reported in [44] does not separate errors caused by the discrepancy between the predicted and real dynamics of the HP and the MN. Therefore, the method from [44] provides high accuracy of UD STF only at a very low level of MN. Under these conditions, the correction of the previous STF is carried out with a weight depending on the current error of STF without taking into consideration the error caused by MN. In this case, the current value of the corrective weight is the inverse of the current variance of the STF error. And the larger this error, the lower the weight value of the adjustment of the previous forecast. In [29], for the STF of processes with UD, MN, it is proposed to choose the value

of the corrective weight for the previous forecast, using the calculation of the value of the Hearst indicator. This indicator, although it makes it possible to assess the nature of the UD of the predicted process, is valid only under certain conditions, which are not always fulfilled under the STF of UD of real processes. At the same time, the specified method for determining the corrective weight does not take into consideration the specific type of process UD. This limits the possibility of improving the accuracy of STF UD, MN. Therefore, a modification of the methods [29, 44] is proposed, which is based on a new method for determining the corrective weight depending on the assessment of the current specific UD of the predicted process against the background of MN, determined on the basis of the averaged current HP RS with UD, MN, only from discrete data preceding the current discrete moment. Let the discrete observations (the UD of the predicted process given the MN) at an arbitrary discrete point in time i be defined as A_i. Then the current RM of the observed data KB_i at a discrete point in time i will be defined by the expression:

$$KB_i = \sum_{j=m}^{i} \frac{\text{if}\left(i \le j, 0, \Phi\left(\varepsilon - \|A_i - A_j\|\right)\right)}{i+1-m}, \tag{1}$$

where $\Phi(*)$ is the Heaviside function; i is the current discrete moment of observation; m is an arbitrary discrete moment of the beginning of the calculation of the current data RS; ε is the value that determines the degree of proximity of the data A_i and A_j. To improve the accuracy of STF UD HP, MN, it is proposed to average the RS (1) in a moving rectangular window of a fixed size W. Then the averaged RS in the moving window (1) KBW_i will be determined from the expression:

$$KBW_i = \text{if}\left[(i-m) < W, 0, \sum_{d=0}^{W} \frac{KB_{i-d}}{W+1}\right]. \tag{2}$$

In accordance with the technique under consideration, it is proposed to use the average estimate (2) as the current weight value to correct the previous forecast. Taking into consideration (1) and (2), the proposed modified STF method for the process with UD, MN, can be represented as the following ratio:

$$\hat{T}_i = \hat{T}_{i-1} + KBW_{i-1}\left(A_i - \hat{T}_{i-1}\right), \tag{3}$$

where $\hat{T}_i$, $\hat{T}_{i-1}$ is a modified forecast at a discrete time point i and $i-1$, respectively, $\left(A_i - \hat{T}_{i-1}\right)$ is a forecast error at a discrete moment i. Ratio (3) differs from the known ones in that the correction of the previous forecast of the process with UD, MS of an unknown level, is carried out with a weight that takes into consideration the UD of the process by calculating the current RS averaged in a moving rectangular window. At the same time, the current weight in ratio (3) is determined at the real rate of acquiring discrete data, which ensures the implementation of STF. Taking into consideration a specific UD in determining the weight of correction of the previous forecast makes it possible to ensure higher accuracy of STF compared to known methods [29, 44].

Thus, the essence of the proposed modification of ZOBM for HP STF with UD, MN of unknown level, is a new technique to determine the current weight of correction of the previous forecast, based on the calculation of the estimate of the average current RS of data observed (2), performed in real time.

The implementation of the proposed modified method of HP STF with UD, MN of unknown level, involves the implementation of three consecutive procedures. The first procedure calculates the current RS values for incoming data A_i according to expression (1). In addition to the incoming data, the procedure involves setting the value of ε, which determines the degree of proximity at which the data A_i and A_j are considered the same at the corresponding points in time. The parameter m in the procedure defines an arbitrary discrete moment to start calculating the current RS of the data. In a particular case, the value of this parameter can be taken to be zero. A given procedure is new for known methods of HP STF with UD, MN of unknown level. The novelty of the procedure is due to the calculation of current RS values for unknown incoming data A_i.

The second procedure involves calculating the results of determining in the first procedure of the current RS values for incoming data A_i of the averaged RS in a moving rectangular window of a fixed size W. The implementation of the second procedure involves setting the size of W for the averaging window. The second procedure is also new to the known methods of HP STF with UD, MN of unknown level. The third procedure involves the formation of a modified HP of the process with UD, MN of unknown level, based on the calculated values of the averaged RS in a moving rectangular window of fixed size W in the second procedure. Its novelty is in the use as a weight correction of the previous forecast of the value of the current averaged RS in a moving rectangular window of a fixed size. The sequence of all steps for this procedure is fully determined in accordance with ratio (3).

Thus, the described procedures implementing the proposed modified method of STF processes with UD, MN of unknown level, in addition to the observed data A_i, require setting the value of W for the averaging window and the value of ε, which determines the degree of proximity of the data A_i and A_j considered at the corresponding points in time, as well as the size W of the averaging window of the current RS of the data. However, setting specific values for these values in the corresponding procedures is not problematic. It should be noted, however, that the value of ε will affect the nature of the representation of the RS plot for specific data, and the size of the averaging window W will affect the degree of smoothing of the current RS of data. General recommendations for the selection of these values can be formulated in the following form: the value of ε should be selected within 20–50 percent of the estimated maximum value of UD, and the size W for the averaging window should not exceed 5 discrete data counts. To verify the adequacy of these recommendations, a numerical experiment was conducted using the test data model described below.

5. 2. Test model of the unknown dynamics of a predicted process and a model of additive masking noise

The test model of the dynamics $A0_i$ was selected as a rectangular pulse of unit amplitude and was determined in the form:

$$A0_i = \Phi(i-n) - \Phi(i-k), \tag{4}$$

where n is the moment of onset of the pulse; k is the moment of the end of the pulse.

As a test model of MN at discrete moments in time, a stationary Gaussian process with a zero average value and

a variable value of SD was selected. A discrete sample N_i of MN of the predefined size was generated using a built-in program in the Mathcad 14 programming environment. The test model (4) of the dynamics is typical in assessing the accuracy of STF and contains the most characteristic for forecasting non-stationary states in the systems of the technical, natural, and social areas.

Taking into consideration these models, the test observed data at discrete times A_i were determined as:

$$A_i = A0_i + N_i. \tag{5}$$

The model of discrete data (5) was subsequently used to assess the accuracy of the proposed modified method and the method reported in [44] for HP STF with UD, MN of various levels.

5. 3. Investigation of the accuracy of the modified method for predicting processes with unknown dynamics masked by noise

The accuracy of STF for the modified method and the method reported in [44] for the test data model (5) was investigated. The choice of these methods is explained by the fact that they both make it possible to predict HP with UD, MN of various levels, in real-time observation. The modeling conditions under which the comparative evaluation of these forecasting methods was carried out were determined by the following data. The accuracy of STF (one step forward) for these methods was determined by an exponentially smoothed estimate of the current absolute prediction errors for test dynamics (4) from observations (5) at discrete moments in time. Exponential smoothing of absolute forecast errors was carried out with a smoothing parameter equal to 80 counts. Simulation of the modified method was performed for $\varepsilon = 0.3$ and $W = 4$. The value of MN SD for the test dynamics (4) ranged from 0.01 to 0.9. The test dynamics (4) during the simulation were determined for the values $n = 200$ and $k = 250$. At the same time, the initial forecast value for the simulated methods was 0.1.

To illustrate the results of the simulation, Fig. 1 shows the dynamics of the smoothed absolute error of STF for the test model of observations (5) at an MN SD of 0.9. The red curve corresponds to the smoothed absolute STF error (E_1) for the modified method, and the black curve corresponds to the smoothed absolute STF error (E_2) for the ZOBM reported in [44].

As an example, Fig. 2 illustrates similar dependences on the dynamics of the smoothed absolute error of the forecast at an MN SD of 0.1.
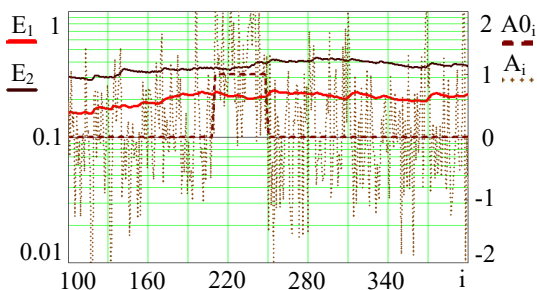

Fig. 1. The dynamics of the smoothed absolute error of prediction based on observations (5) for modified and self-adjusting methods
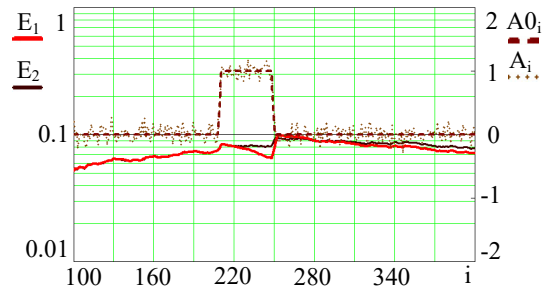

Fig. 2. The dynamics of the smoothed absolute error of prediction based on observations (5) for the modified and self-adjusting methods

In Fig. 1, 2, the dashed line illustrates the current test dynamics of the process $A0_i$, and the dotted line – the test dynamics of the process A_i, taking into consideration the MN, based on which the forecasting is carried out.

6. Discussion of results of studying the prediction accuracy for the modified method

Our study's results show that the provided accuracy of UD STF, MN of various levels is significantly higher for the proposed modified method (less smoothed absolute STF error) compared to known ZOBM [44]. Thus, Fig. 1 shows that for an MN SD of 0.9, the smoothed absolute error of STF for the modified method is not more than 23 %, and for ZOBM – no more than 42 %. This means that the provided accuracy of STF for the test dynamics by the modified method is about twice as high. In the case of noise SD equal to 0.1 (Fig. 2), the smoothed absolute error of STF for both methods is approximately the same and does not exceed 10 %. However, in the region preceding the abrupt decrease in dynamics, the magnitude of the smoothed absolute error of STF is reduced to 1.5 % for the proposed modified method (Fig. 2). This means that at a low level of MN, both STF methods provide approximately the same accuracy. This is explained by the fact that in the case of a small level of MN, the weight of correction of the current forecast for the methods under consideration is determined mainly by UD HP. However, with an increase in the level of MN, ZOBM significantly loses in the accuracy of STF to the proposed method, which takes into consideration UD. At the same time, with an increase in the level of masking noise, it becomes increasingly difficult to assess the dynamics based on MN. This is explained by the fact that with an increase in the noise level, there is large masking by *RS* of the predicted dynamics of HP. However, with a significant level of MN, it makes no practical sense to predict the UD HP. In our opinion, there is no method for forecasting HP with UD, masked by significant noise levels, which would have a high realizable accuracy of STF under these conditions. It should be noted that the proposed modified method of HP STF with UD, MN, is parametric. To implement it, one needs to specify two parameters (ε and W) to calculate the weight of the current correction of the previous forecast. However, the results of the study of the accuracy of STF in the case of the test dynamics under consideration at different values of MN SD showed that the choice of specific values for these parameters has little effect on the resulting accuracy of STF UD, MN. During the research, it was established that for the considered test model of dynamics at different values of MN SD,

the allowable range of values for the ε parameter is from 0.2 to 0.5, and for the *W* parameter – from 1 to 5 samples. Possible areas for the further development of this seminal study might include the verification of the effectiveness of the proposed modified forecasting method and the allowable intervals of the values of the parameters ε and *W* for a wider class of HP test dynamics models and MN models other than the Gaussian process.

7. Conclusions

1. Within the framework of the adaptive zero-order Brown's model, a modified method for predicting hazardous processes with unknown and non-stationary dynamics masked by the noise of various levels, providing increased forecast accuracy, was substantiated. The essence of the proposed modification of the method is a technique for determining the weight of correction of the previous forecast based on the re-current state for the measured data in real-time observation. This makes it possible to correct the previous forecast of unknown dynamics not only taking into consideration the level of masking noise but also taking into consideration information about the current unknown dynamics contained in the current recurrence of the process states.

2. To study the accuracy of the forecast, a test model of the dynamics of the predicted process was determined, as well as a model of additive masking noise with a variable level. The test dynamics of the predicted process were determined in the form of a rectangular pulse with unit amplitude. As an additive model of masking noise, a discrete Gaussian process with a zero mean and a variable value of the mean square deviation was considered. These models were selected as test models when investigating the accuracy of the modified and known methods for predicting a process with unknown dynamics masked by noise with a variable level.

3. The accuracy of the proposed modified and known self-adjusting forecasting methods has been studied. It is shown that the provided accuracy of forecasting unknown dynamics masked by the noise of different levels is significantly higher for the modified method compared to the known self-adjusting method. It has been established that for SD of the masking noise equal to 0.9, the smoothed absolute forecast error for the modified method does not exceed 23 %, and for the known method, the absolute forecast error does not exceed 42 %. In this case, in the case of a masking noise SD of 0.1, the smoothed absolute prediction error for both methods is approximately the same and does not exceed 10 %. That means that at a low level of masking noise, both prediction methods provide approximately the same accuracy. However, with an increase in the level of masking noise, the prediction accuracy of the known method is significantly lower compared to the proposed modified method.

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