УПРАВЛІННЯ У ТЕХНІЧНИХ СИСТЕМАХ

CONTROL IN TECHNICAL SYSTEMS

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APPLICATION OF SINGULAR SPECTRAL ANALYSIS IN CONTROL SYSTEMS OF TECHNOLOGICAL PROCESSES AND EXPLOSION SAFETY CONTROL OF FACILITIES

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ABSTRACT

Context. The question of increasing the productivity of technological processes of extraction, processing and preparation of raw materials, improving product quality, reducing energy consumption, as well as creating safe working conditions during technological processes and preventing accidents is always quite relevant and requires the implementation of modern control and management systems. For the effective operation of such systems, it is important to pre-process and filter the data received from the sensors for monitoring the grinding processes and the explosive status of objects. One of the possible ways to increase the informativeness of data is the use of singular spectral analysis.

Objective. Increasing the efficiency of technological process control systems and the reliability of explosive control systems of coal mines and oil and fuel complex facilities by processing and pre-filtering data received from sensors for monitoring grinding processes and the state of facilities.

Method. To analyze the output signals of sensors used in control and management systems, the method of singular spectral analysis is used, which allows revealing hidden structures and regularities in time series by pre-filtering and data processing of acoustic, thermocatalytic, and semiconductor sensors.

Results. A new approach to the management of technological processes of grinding raw materials in jet mills and control of the explosiveness of coal mines and objects of the oil and fuel complex is proposed, based on methods that allow to speed up the processing speed of sensor output data and improve the quality of information. It is shown that one of the promising methods that can be used for the pre-processing of time series of output data of sensors in control and control systems is the method of singular spectral analysis, the use of which allows filtering data, revealing hidden structures and regularities, and forecasting changes based on the analysis of previous information , identify anomalies and unusual situations, make more informed decisions and improve the processes of managing technological processes.

Conclusions. The conducted experiments have confirmed the proposed software operability and allow recommending it for use in advancing both theoretical and practical aspects of process control systems through an enhanced singular spectral analysis (SSA) method for time series processing. This improved approach has been successfully demonstrated in real-world applications, including grinding processes in jet mills and explosion monitoring in coal mines and oil and fuel facilities. The implementation demonstrates a significant increase in data processing speed and information quality, which makes it particularly valuable for use in safety-critical industrial facilities.

KEYWORDS: control systems, explosion control, sensors, singular spectral analysis, time series.

ABBREVIATIONS

SSA is a singular spectrum analysis.

NOMENCLATURE

$\widetilde{F}^{(k)}$ is an output row;

F is a material time series;

f_i is an element of the time series;

F_n is a restored matrix;

g_k is an intermediate result after diagonal averaging;

i is a i-th index;

j is a j-th index;

K is a sequence of multidimensional vectors obtained through nesting;

L is a length of the window;

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m is a number of non-intersecting subsets;

n is a maximum non-zero number from the eigenvalues of the matrix S;

N is a quantity;

S is a result of the singular decomposition of the trajectory matrix;

U_i is an orthonormal system of matrix eigenvectors S;

V_i is an intermediate result after singular decomposition;

x_{ij} is an element of the matrix;

Y is a $L \times K$ matrix;

λ_i is an eigenvalue of matrix S;

X is a matrix composed of nesting vectors.

INTRODUCTION

Object control and management systems are extremely widely used in industry [1]. They are used to automate production processes, optimize energy consumption, monitor and diagnose equipment, automate warehouses and logistics, ensure workplace safety, control product quality, and manage production resources. These systems help businesses increase productivity, reduce costs and ensure the reliability of production processes, making them more competitive in the market. Application in industry covers a wide range of areas and tasks [2].

There are many types of control and management systems, each with its own advantages and disadvantages, and the choice of a specific type depends on specific tasks and requirements. The main elements of control and management systems are sensors [3]. Nowadays, sensors have become an integral part of our everyday life, surrounding us in various forms and fields of application. Their variety and popularity are explained by their unique capabilities and advantages. Today's sensors are capable of measuring various parameters such as temperature, pressure, humidity, light, speed, sound level, biometrics and much more. They can also operate in a variety of environments, including extreme temperatures, high pressures, and aggressive chemical environments, making them versatile tools in a variety of industries [4].

In terms of speed, sensors are able to transmit information in real time, which is critical in many situations. In industrial processes, the speed of operation of sensors allows you to quickly adjust production parameters and minimize losses. Accuracy of measurements also plays a fundamental role [4]. Sensors in today's world are not only ordinary devices, but also key components that ensure safety, efficiency and convenience in various fields of human activity. Their speed and measurement accuracy contribute to the improvement of our lives and production, making them an integral part of technological progress.

The speed and accuracy of sensors play an important role in many areas of human activity, from industrial processes and medical diagnostics to scientific research and security. These two parameters are fundamental characteristics that determine the usefulness and efficiency of sensors [5]. Sensor speed is critical for automatic control and safety systems. The accuracy of the sensors is also of great importance, especially in areas where small errors can have serious consequences. Combining high accuracy with speed can give the best result, especially in areas where it is necessary to respond quickly to changes in the environment and at the same time ensure high accuracy of measurements. These sensor characteristics play a key role in increasing productivity, ensuring safety, and improving the quality of life in today's world [6].

Sensors monitor various parameters of technological processes, which allows to increase the productivity of the equipment and the quality of products. Accurate measurements of the concentration of explosive gases and vapors are important to ensure the safety of personnel, they can quickly detect gas and fuel leaks and warn of danger, allowing immediate measures to be taken to prevent accidents [7,8]. In these areas, the speed and accuracy of sensors save lives, ensure product quality, and contribute to maintaining the overall level of safety. Considering this, ensuring high accuracy and speed of measurement is an urgent task, the solution of which depends on the final result.

1 PROBLEM STATEMENT

Let the output signal of the sensor represent a time series of numerical data $F = (f_0,....,f_{N-1})$, for example, a chaotic set of acoustic noises that arise during the mechanical interaction of high-energy gas jets with material particles. In order to control the object, it is necessary to select the information components $F^{(k)} = (f_0^{(k)},...,f_{N-1}^{(k)})$ that characterize its mode of operation from the input numerical series. The task is to find effective methods of processing the output signals of the sensors, which allow in real time to carry out preliminary filtering of the data received from the sensors, to isolate the information components necessary for the management of the control objects, to reveal hidden structures and regularities in the time series under the conditions of execution requirements for ensuring the speed of technological process control systems and explosion protection.

2 REVIEW OF THE LITERATURE

Various types of sensors are used in technological process control systems, the output signal of which requires pre-processing to identify the information components that are used to control the process. For example, acoustic sensors are used to control technological processes of grinding raw materials in jet mills [9, 10]. The output signal of these sensors is a chaotic set of acoustic noises that arise during the mechanical interaction of high-energy gas jets with particles of the material to be further crushed. Directly, without preliminary processing of such a signal, it is almost impossible to detect informational signs that characterize the mode of operation of the mill. Therefore, various methods and algorithms for analyzing the signal received from the acoustic sensor are used to analyze the

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output signal. One of the approaches is the use of fuzzy logic [11, 12]. The use of fuzzy logic algorithms for analysis allows you to get a fairly accurate result with a small error of 10%, however, in this approach, the fuzzy logic model is very sensitive to both the quality of the input raw materials and the parameters of the stirrup mill. Thus, the use of a trained model of fuzzy logic allows obtaining a clear result only with optimized input parameters [13]. In [14], the use of the discrete fractional Fourier transform of the discrete type is proposed for the analysis of parameters, the article considers various methods of using this analysis. When they are used on different parts of the signal, these methods show a fairly high accuracy of parameter estimation, but the disadvantage of this method is the need for experimental selection of the method of using the discrete fractional Fourier transform both for different signals and for different parts of the same signal.

Thermocatalytic sensors are widely used in explosiveness monitoring systems [15]. This is due to the high selectivity of such sensors, their low sensitivity to changes in the composition of gases, air humidity, the presence of dust, temperature fluctuations and other external factors. A feature of thermocatalytic sensors is the ability to regulate their operation by changing the power supply parameters, which, together with modern microprocessor devices, allows for computer diagnostics of the performance of control devices and protective shutdown systems. One of the tasks of diagnostics is to identify cases of significant contamination of gas diffusion filters of sensors and intentional restriction of access to them of the controlled environment. Such diagnostics is possible by analyzing the pulsations of the sensor output signal caused by the turbulent mode of movement of the medium – by changing the frequency corresponding to the maximum of the spectral characteristic of the sensor output signal [15], or by evaluating the nature of the transient process after a short-term decrease in the sensor supply voltage [16]. In the first case, the calculation of the frequency requires a preliminary determination of the characteristics of the sensor in the city of installation and subsequent adjustment of the control system, and during the analysis of the transient process, the explosiveness control process is temporarily disrupted.

Semiconductor (metal oxide) sensors are most often used in air purification systems in homes, offices, in ventilation and air conditioning systems [17], as well as in portable electronic devices. Their advantage is high sensitivity, long service life and low cost. However, these sensors are not stable enough, which limits the possibility of their use in explosive control systems and monitoring of working conditions. The instability of the sensors is mainly caused by an incomplete recovery process after exposure to high concentrations of vapors or gases, which leads to a gradual drift of its sensitivity. To reduce the impact, the processing of signals received from the matrix of gas sensors responding to different concentrations of vapors by the method of partial least squares is proposed [18]. However, this significantly complicates control systems, increases their cost and reduces reliability.

The singular spectral analysis method is a methodology for time series analysis that combines elements of classical time series research, analysis of multivariate statistical processes, and data processing in the context of complex systems. All aspects of the SSA methodology, as well as its individual components, can be used for data analysis, depending on the goals of the analysis. Thus, in [19], singular spectral analysis is used for data reconstruction, which made it possible to more accurately and quickly determine the initial components and overall global trends of the initial data of motor learning. In [20], the advantages of using processed SSA data instead of raw data in time series modeling and analysis are considered. It is also proposed to detect data anomalies by analyzing the time derivative of the SSA signal, this is especially relevant when the time derivative is taken from the original data containing noise. The use of a dual methodology to assess both the level and the dynamics of the SSA signal changes helps to identify abnormal situations. In [21], the analysis of the SSA eigenvalue function is used to find the correlation between the components of the input data, which allows finding regularities in them.

3 MATERIALS AND METHODS

Increasing the efficiency of technological process control systems and the reliability of explosive control systems of coal mines and oil and fuel complex facilities is possible by processing and pre-filtering the data received from the sensors for monitoring the grinding processes and the condition of the facilities.

To analyze the output signals of sensors used in control and management systems, the method of singular spectral analysis is used, which allows to reveal hidden structures and regularities in time series by pre-filtering and data processing of acoustic, thermocatalytic and semiconductor sensors of explosive gases and vapors.

Solving the problem of data complexity in object control and management systems requires a comprehensive approach, including the use of modern technologies, algorithms and methods of data analysis, as well as training and development of competencies in the field of data analysis within the organization. by pre-filtering and data processing. To analyze the output signals of sensors used in control and management systems, the method of singular spectral analysis can be used, which allows to reveal hidden structures and regularities in time series.

Singular spectral analysis refers to non-parametric methods of time series analysis. The purpose of the method is to decompose the watch series into interpreted additive components.

Let $N > 2$. Consider a material time series $F = (f_0, ..., f_{N-1})$ of length N. Assuming that the series F is nonzero, that is, there is at least on $f_i = f(i\Delta)$ that is different from zero.

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The basic algorithm consists of two successive, complementary stages: decomposition and restoration. The first stage is decomposition, which in turn is divided into embedding and singular decomposition.

The nesting procedure converts the original time series into a sequence of multidimensional vectors. Let L be some integer (window length), $1 < L < N$. The nesting procedure forms $K = L - N + 1$ nesting vectors:

$$X_i = (f_{i-1},...,f_{i+L-2})^T .$$

When $1 \le i \le K$ have dimension L. These vectors are called L-embedding vectors. We denote by X the matrix composed of embedding vectors:

$$X = [X_1 : ... : X_K] .$$

In other words, the trajectory matrix has the form:

$$X = (x_{ij})_{ij=1}^{L,K} = \begin{pmatrix} f_0 & f_1 & f_2 & \cdots & f_{K-1} \\ f_1 & f_2 & f_3 & \cdots & f_K \\ f_2 & f_3 & f_4 & \cdots & f_{K+1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ f_{L-1} & f_L & f_{L+1} & \cdots & f_{N-1} \end{pmatrix}.$$

Nesting is a standard procedure in time series analysis. After that, this method uses the singular expansion of the trajectory matrix of the series.

Let $S = XX^T$. Denote by $\lambda_1,...,\lambda_L$ the eigenvalues of the matrix S, taken in irreducible order $(\lambda_1 \ge ... \ge \lambda_L)$. Due to the symmetry of the matrix S, it has a real spectrum. We denote by $U_1,...,U_L$ – the orthonormal system of eigenvectors of the matrix S corresponding to the corresponding eigenvalues

Let $n = \max\{i : \lambda_i > 0\}$. If mark:

$$V_i = \frac{X^T U_i}{\sqrt{\lambda_i}}, i = 1,...,d ,$$

then the singular expansion of the matrix X can be written as:

$$X = X_1 + ... + X_d ,$$

where $X_i = \sqrt{\lambda_i} U_i V_i^T$. Each of the matrices has rank 1. Therefore, they can be called elementary matrices.

We will call the set $(\sqrt{\lambda_i} U_i V_i^T)$ the proper triple of the singular expansion.

The decomposition step is followed by reconstruction consisting of clustering and diagonal averaging.

The clustering process divides the entire set of indices $\{1,...,d\}$ into m disjoint subsets based on decomposition $I_1,...,I_m$ based on decomposition. Let $I = \{i_1,...,i_p\}$. Then the resulting matrix X_i, corresponding to the group I, is defined as

$$X_i = X_{i_1} + ... + X_{i_p} .$$

Such matrices are calculated for $I = I_1,...,I_m$, thus the expansion can be written in grouped form

$$X_i = X_{i_1} + ... + X_{i_m} .$$

The procedure for selecting sets $I_1,...,I_m$ i is called the grouping of proper triples.

The last step of singular spectral analysis is diagonal averaging. On it, each matrix of the grouped decomposition is transformed into a new series of length N.

Let Y – be some matrix $L * K$ with elements y_{ij} where $1 \le i \le L$, $1 \le j \le K$. Suppose, $L^* = \min(L, K)$, $K^* = \max(L, K)$ and $N = L + K - 1$. Let $y^*_{ij} = y_{ij}$ if $L < K$, and $y^*_{ij} = y_{ji}$ otherwise. Diagonal averaging translates the matrix Y to a row $g_0,...,g_{N-1}$ – according to the formula:

$$g_k = \begin{cases} \dfrac{1}{k+1}\sum_{m=1}^{k+1} y^*_{m,k-m+2}; 0 \le k \le L^* - 1 \\ \dfrac{1}{L^*}\sum_{m=1}^{L^*} y^*_{m,k-m+2}; L^* - 1 \le k \le K^* \\ \dfrac{1}{N-k}\sum_{m=k-K^*+2}^{N-k^*+1} y^*_{m,k-m+2}; K^* \le k \le N \end{cases} .$$

Applying diagonal averaging to the resulting matrices X_{I_K}, we get $\tilde{F}^{(k)} = (\tilde{f}_0^{(k)},...,\tilde{f}_{N-1}^{(k)})$ and, therefore, the original series $(f_0,..., f_{N-1})$ the original series is decomposed into the sum of m series:

$$f_n = \sum_{k=1}^{m} \tilde{f}_n^{(k)} .$$

The application of singular spectral analysis can help solve the following problems in data processing:

1. Data dimensionality reduction: SSA allows you to decompose a complex time series into its basic components (singular numbers and singular vectors), which reduces the data dimensionality. This simplifies the

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analysis and visualization of the data, and also helps to identify the main components of the time series.

2. Noise and anomaly filtering: SSA can extract the main signal components while ignoring noise and anomalies in the data. This is especially useful if the data contains random variations or artifacts.

3. Highlighting trends and cycles: SSA helps to highlight trends, cycles and seasonal variations in data, which can be important for understanding temporal patterns and forecasting.

4. Time Series Forecasting: SSA-based analysis can be used to forecast future values of a time series based on selected components.

5. Anomaly detection: SSA allows you to compare actual data with model predictions, which can help identify anomalous events or changes in data.

6. Signal and Variability Analysis: SSA can be used for signal analysis, including the processing of temporal data from various sources.

7. Decomposing complex data into components: SSA divides the raw data into a set of components, each representing a different aspect of the time series. This allows for a deeper understanding of the data structure and the identification of key patterns.

8. Exploring data structure: SSA can be used to identify underlying patterns and structure in data, which facilitates data analysis and interpretation.

The application of SSA can significantly simplify the analysis of time data and the processing of complex time series, allowing to explore their structure, highlight key components and reduce the influence of noise.

4 EXPERIMENTS

In order to evaluate the possibility of using singular spectral analysis of acoustic signals, acoustic signals were analyzed for different modes of internal loading of the jet mill. Data from acoustic monitoring of the slag grinding process were used. The following operating modes of the jet mill were analyzed: loading, working mode and unloading.

The standard SSA algorithm assumes a gradual change in the global trend of time series. However, the acoustic signals for the different modes of the jet mill tend to have an initial steep slope due to the fact that most of the learning occurs at the beginning of the adaptation process. In this scenario, we observed that the standard SSA algorithm often fails to accurately capture the initial steepness of the time series. To solve this problem, we applied the Overlap SSA algorithm [22], where the standard SSA algorithm is separately applied to successive overlapping segments of the same length. Considering the computational costs and the requirement for a sufficient time series length in the spectral analysis used in the clustering step, we settled on using only three overlapping segments for the adaptive time series.

Based on the condition of separation of components, we will choose the optimal length of the window L = 4000. Based on the ordered series of eigenvalues of the covariance matrices, we estimate the number of main components necessary to restore the range of the useful signal. In this case, we leave the first ten significant components each, which explain 91.35% of the variance of the output series for the state of jet mill loading (Fig. 1), 93.96% – for the operating mode (Fig. 2), 98.4% – for unloading (Fig. 3).

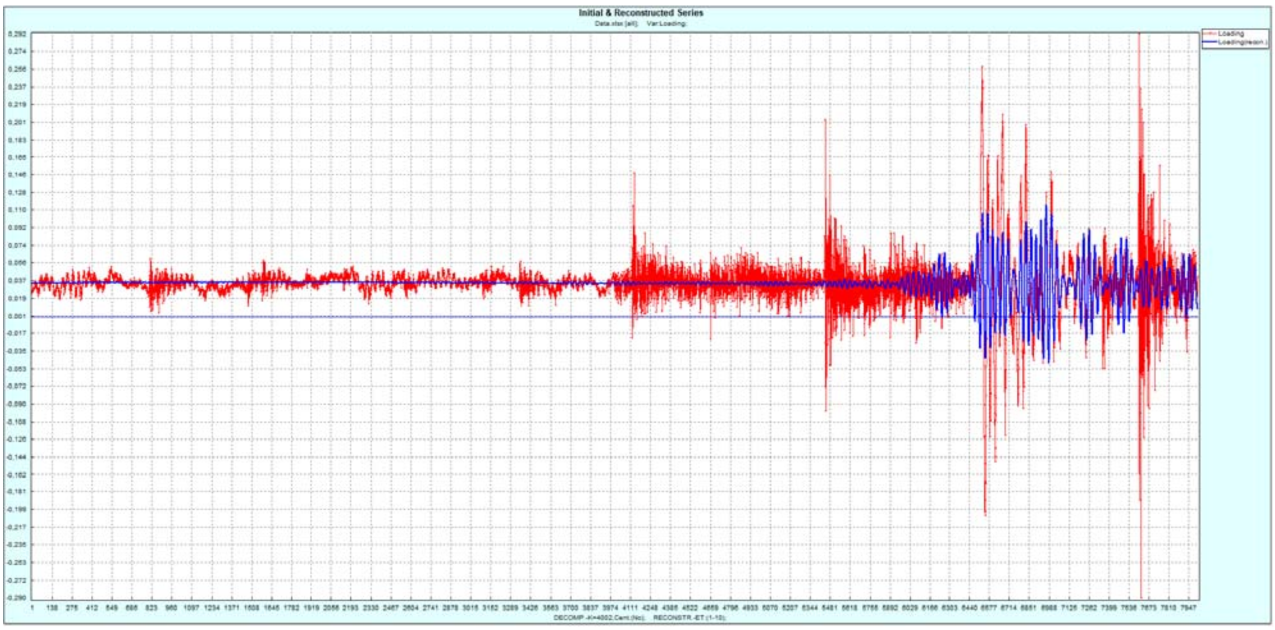

Figure 1 – Mill loading acoustic noise reconstructed by the first ten significant components

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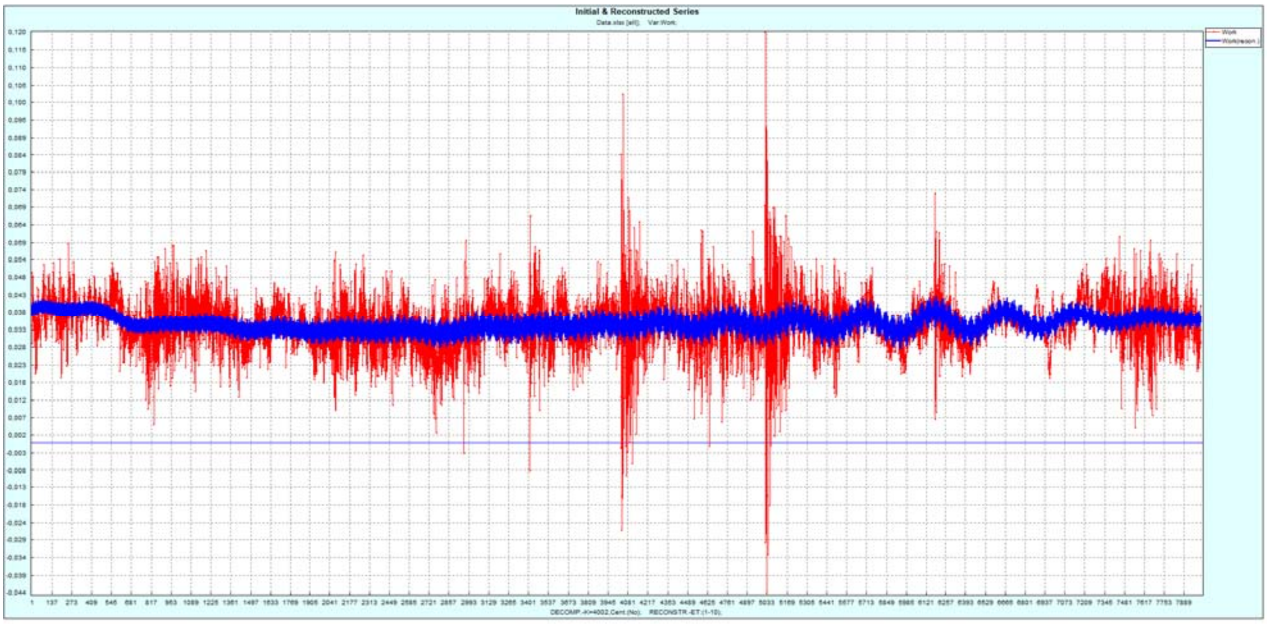

Figure 2 – Acoustic noise in the operating mode reconstructed by the first ten significant components

Based on the fact that more than 90% of the variances of the output series are contained in their first ten significant components at different operating modes of jet mills, it is advisable to use the definition of the main significant components that carry the main informativeness of acoustic signals for the classification of acoustic signals arising during the operation of jet mills, and control their loading.

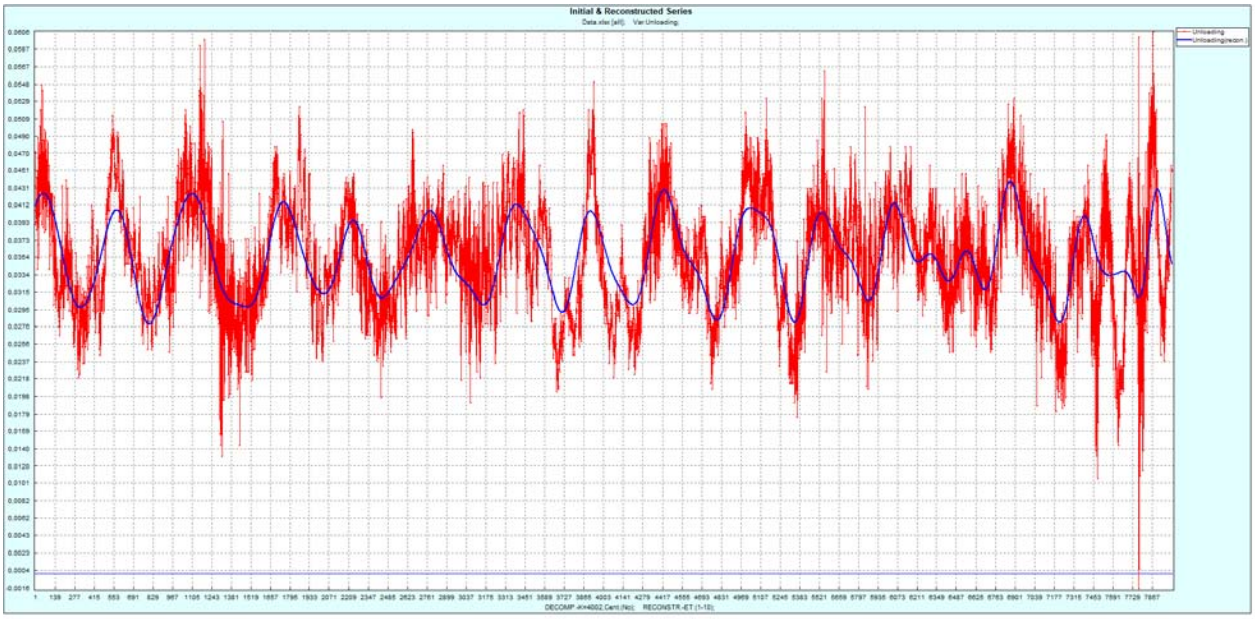

Figure 3 – Acoustic noise during mill unloading reconstructed by the first ten significant components

In order to assess the possibility of using singular spectral analysis in explosiveness control systems for filtering noise and anomalies, as well as to detect cases of significant contamination of gas diffusion filters of sensors and limiting access to them of the controlled environment, the monitoring data of the output signals of the sensors in different modes of their operation were analyzed.

The actual raw output signal of the sensors (Fig. 4) always contains noise and anomalies due to the influence of industrial sources of electromagnetic disturbances. In order to simplify the processing of the information coming from the sensors and offload the computing resources of the explosion monitoring systems, it is advisable to isolate the main signal components, ignoring noise and anomalies in the data. SSA can extract the main signal components while filtering out noise and

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anomalies. In Fig. 5 shows the results of SSA processing of the sensor output signal in the absence of directional movement of the controlled medium. The sensor signal reconstructed by the first two significant components reflects the dynamics of changes in the concentration of the explosive component in the air. At the same time, the signal is filtered from uninformative noises and anomalies.

The output signal of the sensor is actual and restored according to the first two significant components in the presence of directional movement of the controlled environment (Fig. 6) also reflects the dynamics of changes in the concentration of the explosive component in the air and is filtered from noise and anomalies. In its turn, reconstructed according to the first seven significant components (Fig. 7), the same sensor signal contains a harmonic component due to the presence of macroturbulent disturbances in the controlled environment.

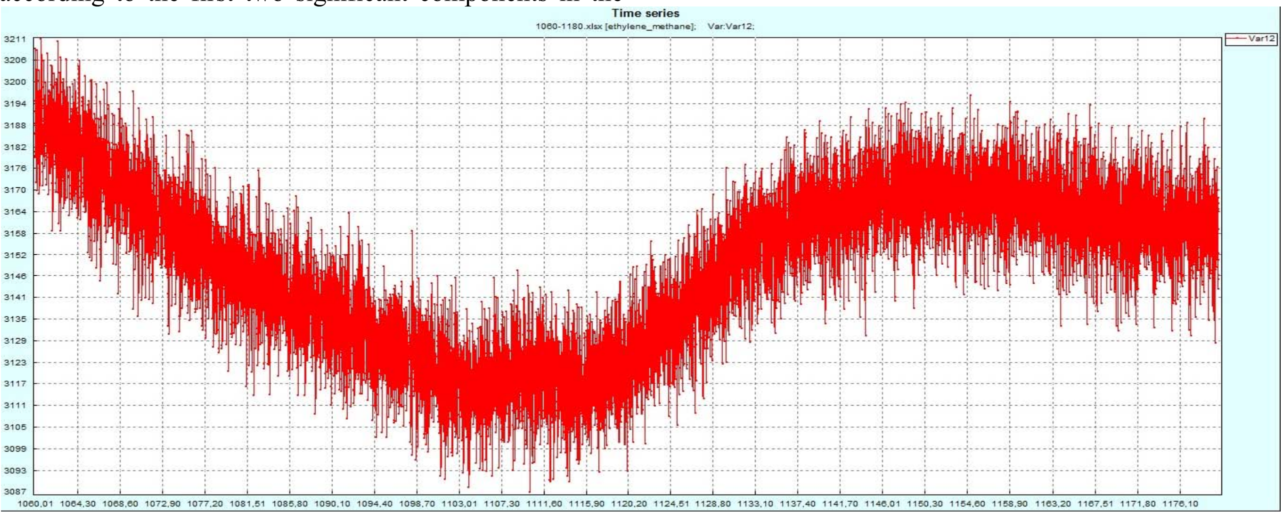

Figure 4 – Actual raw sensor output

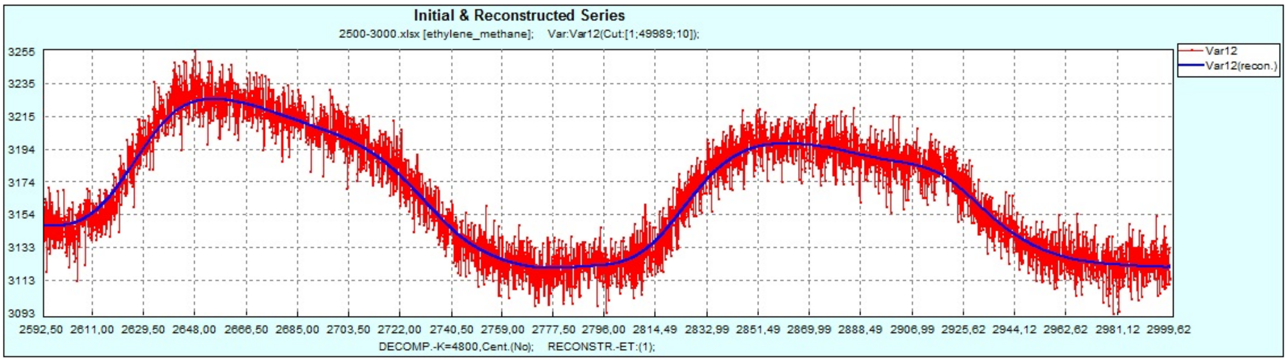

Figure 5 – Sensor output signal actual and restored by the first two significant components in the absence of directional motion of the monitored medium

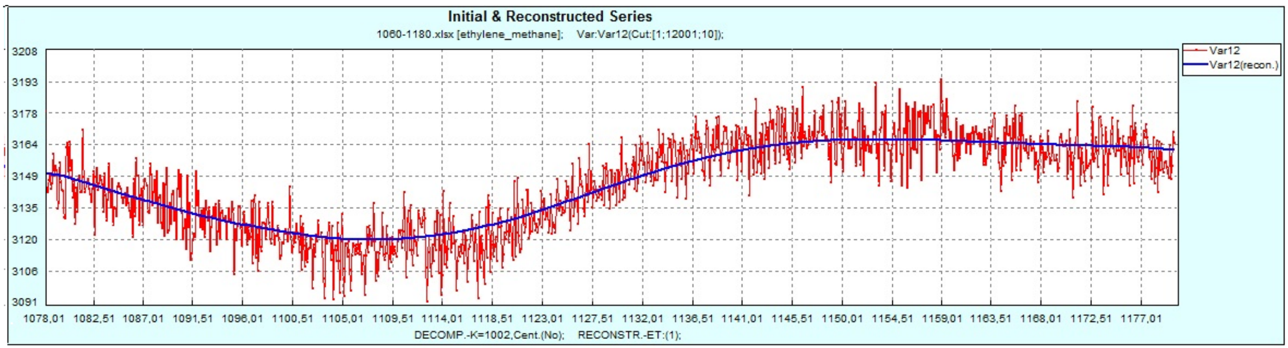

Figure 6 – Sensor output signal actual and restored by the first two significant components in the presence of directional motion of the controlled medium

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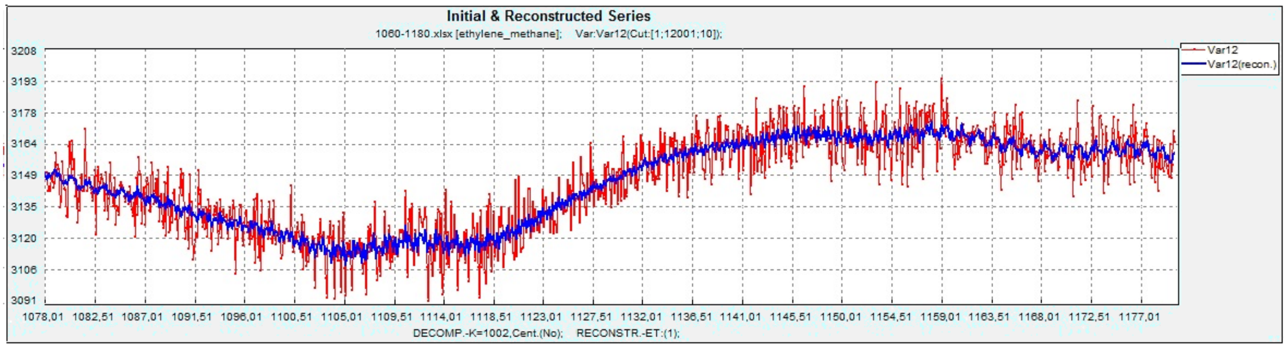

Figure 7 – Sensor output actual and restored by the first seven significant components in the presence of controlled medium motion

5 RESULTS

Thus, by decomposing difficult-to-analyze signals into components, SSA divides the raw data into a set of components, each representing a different aspect of the time series. In this case, the appearance of a harmonic component when restoring the signal by the first seven significant components indicates the presence of a directional movement of the medium. The frequency of macroturbulent disturbances at constant geometric dimensions of the flow depends on the speed of the medium, and the relative amplitude of the harmonic component depends on the diffusion conductivity of the sensor filters [14]. In the future, the use of SSA in explosion control systems allows to significantly expand their functions, including detecting significant pollution of gas diffusion filters of sensors, cases of restricted access to them of the controlled environment and changes in location, detecting fuel-air emissions at the facilities of the oil and fuel complex and evaluating them volumes All this determines the need for further research in this direction.

The proposed approach to managing technological processes of grinding raw materials in jet mills and controlling the explosiveness of coal mines and objects of the oil and fuel complex makes it possible to speed up the processing speed of sensor output data and improve the quality of information. One of the promising methods that can be used for preliminary processing of time series of output data from sensors in control and control systems is the method of singular spectral analysis.

6 DISCUSSION

The use of singular spectral analysis in technological process control systems and control of the explosiveness of objects allows to improve such criteria as:

1. Management of technological processes. Singular spectral analysis makes it possible to distinguish the main components in complex systems, which contributes to more accurate and efficient management of production processes. This is especially important in the conditions of modern high-tech industries, where the complexity and scale of technological processes require new approaches to management.

2. Safety of explosive objects. In the context of industrial safety, singular spectral analysis has been applied to the analysis and control of parameters related to explosiveness. Accurate and timely data on changes in technological processes allow you to warn about potential dangers or other factors that can cause accidents.

3. Automation and monitoring. The use of singular spectral analysis in control systems allows for the automation of monitoring and control processes, which reduces the probability of human errors and ensures a higher sensitivity of the system to changes in the production environment.

4. Reduction of risks and economic benefits. Early detection of potential problems in technological processes and quick response to them reduces the risk of accidents, increases overall safety and economic efficiency of production.

CONCLUSIONS

The performed studies showed the relevance of the use of singular spectral analysis for the analysis of time series obtained in technological process control systems. The application of singular spectral analysis is a powerful tool for processing and analyzing time data. Decomposing complex time series into basic components, such as singular numbers and vectors, using SSA provides effective data dimensionality reduction. This greatly simplifies the task of data analysis and visualization, allowing to highlight the main structural elements of the time series. SSA also excels in its ability to filter out noise and anomalies, which is a valuable aspect when dealing with real-world data prone to random variations. In addition, the application of SSA expands the analytical possibilities for highlighting trends, cycles and seasonal fluctuations in the data. This method is useful for forecasting future values of time series and contributes to a deeper understanding of temporal patterns. SSA opens up new possibilities in the analysis of temporal data by providing tools for extracting key components, exploring data structure, and reducing the influence of noise, which together make it a valuable technique in process control systems.

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ЗАСТОСУВАННЯ СИНГУЛЯРНОГО СПЕКТРАЛЬНОГО АНАЛІЗУ В СИСТЕМАХ КЕРУВАННЯ ТЕХНОЛОГІЧНИМИ ПРОЦЕСАМИ ТА КОНТРОЛЮ ВИБУХОНЕБЕЗПЕЧНОСТІ ОБ'ЄКТІВ

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АНОТАЦІЯ

Актуальність. Питання підвищення продуктивності технологічних процесів видобутку, переробки та підготовки сировини, поліпшення якості продукції, зниження енерговитрат, а також створення безпечних умов праці при веденні технологічних процесів та попередження аварій завжди є досить актуальним і потребує впровадження сучасних систем контролю і управління. Для ефективної роботи таких систем важливою є попередня обробка та фільтрації даних, отриманих від датчиків контролю процесів подрібнення та стану вибухонебезпечності об'єктів. Одним із можливих шляхів підвищення інформативності даних є застосування сингулярного спектрального аналізу.

Мета. Підвищення ефективності систем керування технологічними процесами та надійності систем контролю вибухонебезпечності вугільних шахт та об'єктів нафто-паливного комплексу шляхом обробки та попередньої фільтрації даних, отриманих від датчиків контролю процесів подрібнення та стану об'єктів.

Метод. Для аналізу вихідних сигналів датчиків, які використовуються в системах контролю та управління використаний метод сингулярного спектрального аналізу, який дозволяє виявити сховані структури та закономірності в часових рядах шляхом попередньої фільтрації та обробки даних акустичних, термокаталітичних та напівпровідникових датчиків.

Результати. Запропоновано новий підхід до керування технологічними процесами подрібнення сировини в струминних млинах та контролю вибухонебезпечності вугільних шахт і об'єктів нафто-паливного комплексу на основі методів, що дозволяють пришвидшити швидкість обробки вихідних даних датчиків та підвищити якість інформації. Показано, що одним із перспективних методів який можливо використати для попередньої обробки часових рядів вихідних даних датчиків в системах керування та контролю є метод сингулярного спектрального аналізу, використання якого дозволяє здійснити фільтрацію даних, виявити сховані структури та закономірності, здійснювати прогнозування змін на основі аналізу попередньої інформації, виявити аномалії і нештатні ситуації, приймати більш обґрунтовані рішення та поліпшити процеси керування технологічними процесами.

Висновки. Проведені експерименти підтвердили працездатність запропонованого програмного забезпечення та дозволили рекомендувати його для використання в розвитку як теоретичних, так і практичних аспектів систем керування технологічними процесами за допомогою вдосконаленого методу сингулярного спектрального аналізу (SSA) для обробки часових рядів. Цей удосконалений підхід був успішно продемонстрований у реальних застосуваннях, включаючи процеси подрібнення на струминних млинах і моніторингу вибухонебезпечності на вугільних шахтах та підприємствах нафто-паливного комплексу. Впровадження демонструє значне підвищення швидкості обробки даних і якості інформації, що робить його особливо цінним для застосування на критично важливих для безпеки промислових об'єктах.

КЛЮЧОВІ СЛОВА: системи керування, контроль вибухонебезпечності, датчики, сингулярний спектральний аналіз, часові ряди.

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