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NUMERICAL ANALYSIS OF TIME SERIES OF THE MINE AIR PARAMETERS

ANALIZA NUMERYCZNA SZEREGÓW CZASOWYCH PARAMETRÓW POWIETRZA KOPALNIANEGO

Implemented in coal mines, the systems for monitoring and control of gas hazards and ventilation performance provide a great number of data onto the surface. The purpose of those systems is current control maintained by the mine's dispatch service in relation to the mine atmosphere, and in particular in the aspects of potential methane and fire hazards. As the test had proved (Dziurzyński, Wasilewski 1999), such data may be also applied for both the analyses and prophylactic-preventive measures carried out by ventilation services in mines.

This paper presents is the analysis of time series of signals from measurement of the mine air, registered in systems for monitoring and control of ventilation. Observation of the signals representing physical-chemical parameters of the mine air (pressure, air flow velocity or gases CH_4, CO, and smoke concentration) prove that the above are subjected to disturbances of random amplitude and duration. Reliability and effectiveness of the analyses being carried out require both the information on properties of physical-chemical parameters of mine air and identification of the signals' frequency/time structure. Occurrence of the random disturbances in ventilation process and insufficient knowledge of the venue structure bring about a necessity of the statistic methods of identification to be applied in practice. A significant advantage of the statistic methods of processes identification (Mańczak 1971) may be the fact that their application does not require experiments, but is based on data registered in conditions of the venue's regular operation. These are just the most appropriate methods that enable to evaluate characteristics of the objects subjected to non-measurable random disturbances.

For this purpose a numerical analysis of measuring data, based on the correlation-spectral theory of stationary stochastic processes is proposed. The air physical-chemical parameters are the continuous realisation of the stochastic process observed only at discrete moment in time, because in computerised monitoring systems they are subjected to sampling with a fixed frequency, giving a sequence of real numbers that form a time series.

As a result of the numerical analysis of a stochastic process the characteristics of signals (Bendat, Piersol 1976; Otnes, Enochson 1978) with regards to amplitude (statistical analysis), time (correlative analysis) and frequency (spectral analysis) were determined. In the correlative-spectral analysis of time series the calculation algorithms based on the discrete Fourier transform are applied.

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Independently of individual signals testing, the paper presents the results of testing of interdependencies between signals registered at various points of the mine workings network. So obtained information may be applied to the multi-aspect identification of the network parameters, with the use of signals correlation. The numerical analysis of time series in a complex network may be also used (Wasilewski 1998) for evaluation and balance of gases being released during of exploitation work, e.g. shooting, or gas-dynamic phenomena caused by rapid outflow of methane due to bump, methane breakout or explosion (Report of the Commission WUG, 2002).

Key words: numerical analysis of signals, ventilation measurements, air parameters, mine ventilation

Zainstalowane w kopalniach systemy monitorowania i kontroli zagrożeń gazowych i stanu wentylacji dostarczają na powierzchnię dużą liczbę danych. Celem tych systemów jest doraźna kontrola przez dyspozytorów kopalń stanu atmosfery kopalnianej, szczególnie pod kątem zagrożeń metanowych i pożarowych. Doświadczenia pokazują (Dziurzyński, Wasilewski 1999), że dane te mogą być również wykorzystywane przez służby wentylacji kopalń do analiz i działań profilaktyczno-prewencyjnych.

W artykule przedstawiono analizę szeregów czasowych sygnałów pomiarowych parametrów powietrza kopalnianego rejestrowanych w systemach monitorowania i kontroli wentylacji. Obserwacja sygnałów reprezentujących parametry fizyczno-chemiczne powietrza kopalnianego (ciśnienie, prędkość powietrza czy stężenie gazów CH_4, CO, oraz dymu) pokazują, że podlegają one silnym zakłóceniom o przypadkowej amplitudzie oraz czasie trwania. Wiarygodność i skuteczność wykonywanych analiz wymaga zarówno informacji o właściwościach parametrów fizyczno-chemicznych powietrza kopalnianego, jak i znajomości struktury częstotliwościowo-czasowej sygnałów. Występowanie przypadkowych zakłóceń w procesie wentylacji oraz niedokładna znajomość struktury obiektu powodują konieczność stosowania w praktyce statystycznych metod identyfikacji. Istotną zaletą statystycznych metod identyfikacji procesów (Mańczak 1971) jest fakt, że nie wymagają one dodatkowych eksperymentów, ale wykorzystują dane rejestrowane w warunkach normalnej eksploatacji. Właśnie te metody pozwalają na ocenę właściwości obiektów poddawanych niemierzalnym zakłóceniom przypadkowym.

W tym celu proponuje się analizę numeryczną danych pomiarowych opartą na teorii korelacyjno-widmowej stacjonarnych procesów stochastycznych. Parametry fizyczno-chemiczne powietrza są ciągłymi realizacjami procesu stochastycznego obserwowanymi tylko w dyskretnych chwilach czasu, ponieważ w komputerowych systemach monitorowania podlegają próbkowaniu z ustaloną częstotliwością, dając ciąg liczb rzeczywistych stanowiących szereg czasowy. W wyniku analizy numerycznej procesu stochastycznego wyznacza się zdeterminowane charakterystyki sygnałów (Bendat, Piersol 1976; Otnes, Enochson 1978) w dziedzinie amplitudy (analiza statystyczna), czasu (analiza korelacyjna) oraz częstotliwości (analiza widmowa). W analizie korelacyjno-widmowej szeregów czasowych wykorzystuje się algorytmy obliczeniowe oparte na dyskretnym przekształceniu Fouriera.

W artykule niezależnie od badania pojedynczych sygnałów dokonano również badania zależności wzajemnych sygnałów rejestrowanych w różnych punktach sieci wyrobisk kopalnianych, które mogą być szeroko wykorzystywane do identyfikacji parametrów sieci z wykorzystaniem korelacji wzajemnej sygnałów. Analiza numeryczna szeregów czasowych w złożonej sieci może być również wykorzystywana (Wasilewski 1998) do oceny i bilansu gazów wydzielających się w czasie prowadzenia robót eksploatacyjnych, np. strzelania czy zjawisk gazodynamicznych wywołanych nagłym wypływem metanu w wyniku tąpnięcia, wyrzutu czy wybuchu metanu (Sprawozdanie Komisji WUG, 2002).

Słowa kluczowe: analiza numeryczna sygnałów, pomiary wentylacyjne, parametry powietrza, wentylacja kopalń

1. Introduction

A ventilation network of a contemporary deep coal mine is an extensive spatial network that comprises several hundred air splits of the total length exceeding several hundred kilometres. Production processes in mines cause changes in both the network structure and workings geometry. The air flow within a ventilation network is subjected to numerous disturbances resulted from the external factors, among other things mining operations, changes occurred in the atmospheric air and in geological-mining conditions, and from the internal factors, for instance changes in the air splits resistance, emission of gases, generation of shooting gases, etc. So the ventilation network is a complex spatial system in which the dynamic process is a subject to numerous and variable disturbances. The majority of these disturbances are of random character regarding their amplitude, place of occurrence and their duration, therefore a ventilation process is regarded as a stochastic process (Krzystanek, Szywacz, Wasilewski 1984; Szywacz 2001; Wasilewski 1986).

Testing performed within monitoring and gas hazardous systems enabled to recognise the structure of ventilation process disturbances in mines. It has been proved (Wasilewski 1986) that, among others, these disturbances are of additive character, and that in the aspect of their duration can be divided into three basic types:

- disturbances of high change rate, of their duration time measured in minutes, caused by the accidental occurrences in the system, e.g. motion of train cars and mine cage, shooting, opening or shutting of dams — all these events cause only momentary variations in the network state,
- quasi-deterministic disturbances, of duration time measured in hours and of a cyclic character, caused by the technological actions, mostly the getting machines operation,
- disturbances of low change rate, of duration time measured in days and weeks, caused by changes in the structure and geometrical parameters of mine workings, or changes in atmospheric conditions and efficiency of gas sources — such disturbances result in permanent changes in the state of process.

At the same time, observations performed in the coal mines proved that a flow of large volumes of the mine air of considerably low velocity results in the process inertia being expressed as considerable damping of disturbances, in particular those of short duration and little amplitudes. Disturbances of the air velocity and methane or carbon monoxide concentration occurred in the regions of mine production and caused by disturbances of the airing process conditions, changes in gas emission or other events related to the mining production, e.g. shooting (Szywacz 2001), are of local and momentary character, and diminish as the air flows towards upcast shaft, e.g. post-shooting curves of methane or carbon monoxide concentration. This enables to consider a ventilation process as being the process with low change rate, subjected to numerous disturbances, which assumption is consequently used in further analysis of the process regarded as a stochastic process.

Momentary state of the ventilation process is being described by momentary values of its parameters. Taking into consideration the character of disturbances, one can assume, as it has been usually made for a process with the low change rate, that a momentary state is being described by average values of the process parameters as well as their momentary or periodic disturbances. The average values of parameters determine certain state that for a process with low change rate is named the process state of equilibrium. Inertia of the ventilation process causes that its local disturbances have not a significant impact on its state of equilibrium. Whereas disturbances of long duration cause slow variations in the average values of the process parameters, and this way affect its state of equilibrium.

When considering any parameter of the process in any point of a mine, e.g. in the mining operations area, one can say about its average value as representing the state of equilibrium, whereas about its random component as representing the disturbance of this parameter. This assumption enables to consider a random component of parameter (i.e. after elimination of its low change rate component) in any chosen point, e.g. a region independently of other points of ventilation network, and to make its analysis on the basis of observation in short periods of time. On the other hand, eliminating high change rate components one can observe the state of equilibrium of process in the mine ventilation system and track out its changes, with consideration of the structural interdependencies and principles that rule the mine air flow in the system. This method results in certain decomposition of the issue of testing ventilation process in time and space that shall justify the assumed way of analysing parameters in a complex ventilation process. This approach and assumption have been adopted for making analysis of measuring signals registered in the mine air parameters monitoring systems (Wasilewski 1986).

2. Aim and scope of the measuring signals analysis

Analysis of any measuring signal requires assuming certain mathematical description, i.e. the signal model. Here a stochastic process of continuous realisations was assumed as the signal model. One-dimensional real stochastic process X is a representation having values in the real number set R determined for product $\Omega \times T$ of the elementary events space Ω and the set T being the real number set R or a subset considered as a time interval, if for each determined moment $t \in T$, the representation X_t, considered as a function of argument $\omega \in \Omega$, is a random variable (Plucińska, Pluciński 1981). So the stochastic process X may be considered as a family of random variables indexed with the real parameter t, i.e. $X = \{X_t\}_{t \in T}$. For each event $\omega \in \Omega$ the representation x_ω, determined on interval T with values in the real number set R, is named a realisation of the stochastic process. Therefore stochastic process X can be also considered as a family of realisations indexed with the elementary events ω, i.e. $X = \{x_\omega\}_{\omega \in \Omega}$.

If one considers the stochastic process X as a family of random variables $\{X_t\}$, then the full probabilistic characteristics of the process value for each moment t shall be distribution of the random variable X_t related to moment t. The exhaustive description of a stochastic process shall be presenting of its all definitely dimensional distributions of values for each possible configurations of moments that means determination of its definitely dimensional distribution functions. However, practical use of probability distributions is difficult and complicated. Usually one may use certain simple parameters that relate to distributions. These are among others, like for random variables, average value, variance and correlation of the stochastic process defined for representation of a process in a form of a family of random variables, i.e. $X = \{X_t\}_{t \in T}$. A certain specific type of stochastic processes shall be of significant importance for both theoretical consideration and practical issues. This is a stationary process of which all probabilistic characteristics do not change with any movement of the time axis. In practice, in most cases one has only few observations of stochastic processes at his disposal that represent the particular fragments of its realisation limited in time. A significant characteristic of the stochastic processes that enable to estimate values of their parameters on the basis of its single realisation is ergodicity (as said colloquially, that "parameters calculated after time are equal to parameters calculated after/outside set").

If one wishes to analyse signal by computer methods, one has to carry out sampling observations in such way as to obtain a sequence of real numbers suitable for numerical analysis, constituting a time series of the process.

Sampling of the signal observation is realised by measuring the continuous signal's values in defined intervals (sampling period) in such way as to obtain a series of samples that enables to represent the signal in the most accurate way. This is possible thanks to the Kotielnikow-Shannon theorem on sampling of the signal (Szbatin 1982; Wojnar 1980) that reads that each continuous signal of limited frequency spectrum may be accurately represented (recreated) on the basis of its momentary values given together with period of sampling $T = 1/(2 \cdot F)$, where F is the highest frequency transmitted by the signal. Obtained definite sequence of samples shall be a discrete representation of signal. In practice, in the monitoring and control systems of industrial process parameters, sampling takes place in a natural way. Signals are being sampled within the period resulting from duration of the cycle time of automatic measurement of a given quantity.

For the analysis to be effective (Bendat, Piersol 1976; Szbatin 1982) the observed measuring signals should represent stationary or non-stationary character of the process adequately, i.e. the observation time of a signal should be sufficiently long compared with the period of signal component of the lowest frequency that enables to distinct non-stationary trends from random variations of the signal.

The objective of the numerical analysis of measuring signals with the model of stochastic process form is to establish determined characteristics that describe the analysed process (Bendat, Piersol 1976; Mańczak 1971; Otnes, Enochson 1978). On the basis of time series representing a stochastic process, it is only possible to estimate the deterministic characteristics searched for. For the stationary and ergodic processes one can effectively determine them on the basis of single realisation, and relate the estimations of characteristics to the stochastic process.

Introduction to the time series analysis shall be examination of its stationarity. In the assumed model we use the notion of a weak stationarity, i.e. stationarity in relation to the average and average-quadratic values. If a time series proves to be non-stationary, then one has to eliminate the occurring non-stationarity and analyse only the stationary component.

The scope of analysis of a stationary time series shall comprise:

- statistic analysis (regarding amplitude),
- correlative analysis (regarding time),
- spectral analysis (regarding frequency).

The scope of statistic analysis shall comprise, above all estimation of the average value and variance, also the maximum and minimum values and the density of probability distribution. The average value shall indicate the level of a process, whereas variance — of its intensity. The average value represents a static, independent on time, component of the process and variance represents dynamic component, i.e. changes of momentary values in relation to average value. The maximum and minimum values enable to determine the range of momentary values changeability. The purpose of determination the forms of probability distribution density is to establish statistic principles relating to the signal momentary values. The probability density describes probability of the event in such way that the signal values are within certain determined range.

The basic purpose of correlative analysis is to estimate correlation function, in case of analysis of individual signal called autocorrelation function, which characterises the general dependency of the signal value in certain determined moment on its value in other moment. The most important application for the correlation function is examination leading to establishing to what extent the process values in certain determined moment shall impact the process values in certain moment in future. The correlation function is being applied extensively for the analyses of signals, because it enables, among others, to evaluate their randomness level. It means that the correlation function for a random process approaches zero with the big values of displacement. The latter causes that function of correlation makes a perfect tool to detect the determined processes that may be concealed by random noise. The other but not less important characteristic of the autocorrelation function is reproduction of the periodicity of the original run while retaining its period, which can be applied to detecting the periodic components of the analysed signals.

The purpose of spectral analysis is to estimate function of spectral density that describes the general frequential structure of the process. The frequent application of the spectral analysis is to differentiate a periodic signal from the random signal.

For the purpose of realisation of a continuous stationary process, there are defined:

- Average value

$$\bar{x} = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t)dt \tag{1}$$

- Variance

$$s^2 = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} [x(t) - \bar{x}]^2 \, dt \tag{2}$$

- Correlation

$$R(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} x(t)x(t+\tau)dt \tag{3}$$

- Spectral density

$$S(\omega) = \int_{-\infty}^{\infty} R(\tau)e^{-j\omega\tau} d(\tau) \tag{4}$$

that is a Fourier transform of the correlation function R.

And the inverse Fourier transform gives the following relation

$$R(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S(\omega)e^{j\omega\tau} d\omega \tag{5}$$

Usually utilised is one-sided spectral density G given with a relation

$$G(\omega) = 2S(\omega) \tag{6}$$

Thus, both the spectral density function and correlation function provide similar information on the process in the aspect of frequency and time, respectively. For a stationary process both above-mentioned functions are equivalent as regards information contained therein, but provide information in different forms and for the purpose of the specific problem solution the more appropriate may be one of these forms.

The measure of linear relationship among random variables is the cross-correlation function. The basis distinction between the cross-correlation function and autocorrelation function is that the cross-correlation function may reach its maximum value not necessarily for the displacement $\tau = 0$. Since for the cross-correlation function the relative phase of runs is retained, so in practice, if for the certain value of the displacement t both runs are similar, then the maximum of cross-correlation function occurs. Thanks to this propensity, the cross-correlation function enables to determine the time inter-dependencies among signals, i.e. in a form of the signals propagation delays.

In the process identification, the cross-correlation function is being applied for detection and recovery of the signal concealed in noise, even in case when such signal is not of a periodical nature. Process of determination the cross-correlation function may be therefore considered as a filtration process.

3. Calculation methods and algorithms of the time series analysis

Assumption of a measuring signal model in a form of stochastic process implies application of specific methods for the analysis of measuring data. These are the methods of correlative-spectral theory of stochastic processes, designed for stationary processes (weakly, in broader sense).

Let us assume, that we have at our disposal a time series $\{x_i\}$, $i = 1, ..., n$, representing certain stochastic process X weakly-stationary. In general, the process X may be a part of the certain non-stationary process Y. Of course, if the process is ergodic, then the obtained values of time series parameters may be generalised onto the whole process and then represent evaluations of the stochastic process parameters.

In the correlative-spectral analysis of time series one should use the discrete Fourier transform given with the following relation (Bendat, Piersol 1976; Otnes, Enochson 1978):

$$X_k = \Delta t \sum_{i=0}^{n-1} x_i e^{-j\frac{2\pi i}{n}k}, \qquad k = 0, 1, ..., \frac{n}{2} - 1 \tag{7}$$

Observation time interval $[0, T]$ is divided into n-number of sub-intervals of length Δt equal to the sampling period, and the frequency range $[0, \frac{\Delta t}{2}]$ divided into $\frac{n}{2}$ sub-ranges of length $\Delta f = \frac{1}{n \cdot \Delta t}$ equal to the basic frequency, because the unique results occur only for frequencies lower then the Nyquist limit frequency equal $\frac{1}{2\Delta t}$.

The inverse discrete Fourier transform is given with the following relation (Bendat, Piersol 1976; Otnes, Enochson 1978):

$$x_i = \Delta f \sum_{k=0}^{n-1} X_k e^{j\frac{2\pi i}{n}k}, \qquad i = 0, 1, ..., n-1 \tag{8}$$

Letter j in the formulas (7) and (8) means the imaginary unit.

Comments to the point of the weak stationarity and ergodicity of time series. A time series of finite variance is weakly-stationary when its average value is not time-dependent and correlation depends only on the time difference, i.e. displacement. The weakly-stationary time series of the average value equal zero is weakly ergodic when its correlation function is a continuous function that fulfils the following condition: $|R(\tau)| \to 0$ for $\tau \to \infty$. This gives a possibility to test a weak ergodicity of the time series. If the obtained estimator of correlation function can be approximated with the function of a form $b \cdot e^{-a|\tau|}$ or $b \cdot e^{-a|\tau|} \cdot \cos(\omega \cdot \tau)$, then the series is weakly-ergodic (Mańczak 1971).

3.1. Testing of stationarity and elimination of non-stationarity

For testing of stationarity of the time series $\{x_i\}$, $i = 1, \ldots, n$, the stationarity test based on the number of series calculated in relation to median of values of time series was used (Bendat, Piersol 1976; Greń 1974).

If a time series is non-stationary, then such non-stationarity should be eliminated. Elimination of non-stationarity is usually carried out (Krzystanek, Szywacz, Wasilewski 1984; Szywacz 2001; Wasilewski 1986) by means of low-pass digital filtration with use of Brown's filter of the first order (Bendat, Piersol 1976; Otnes, Enochson 1978) described with the recurrent equation:

$$y'_i = \alpha y'_{i-1} + (1-\alpha) y_i, \qquad i = 1, 2, \ldots, \qquad y'_0 = y_1 \tag{9}$$

whereas filtration coefficient α is a real number of interval (0,1).

In the more complex cases (Szywacz 2001) the non-stationary average value may also be eliminated by way of approximation of the values of time series with any chosen function $y(t; a,b,\ldots)$ of one variable (time) dependant on parameters a, b, ...; (the values of coefficients a, b, ... one can determine on the basis of the measurement series $\{y_i\}$, $i = 1, \ldots, n$), using the average-quadratic approximation method. The sum should be minimised (Findeisen, Szymanowski, Wierzbicki 1980)

$$S(a,b,\ldots) = \sum_{i=1}^{n} [y(t_i; a,b,\ldots) - y_i]^2 \tag{10}$$

in relation to parameters a, b, ...

The time series representing the mine air parameters proved to be of non-stationary nature (Szywacz 2001; Wasilewski 1986). Having disregarded the transient states of parameters (CO, CH_4) caused, for instance by shooting, fire or regulations of the air propagation (Szywacz 2001; Wasilewski 1986, 1998) that as themselves are non-stationary, we have performed the analysis of time series with the exclusion of those disturbances. The occurrence of non-stationary low change rate components (the average value of parameters variable in time), that according to the former assumptions of the analysis represent low-rate changes in the process state of equilibrium, was proved.

Eventually, the time series of all air parameters can be described with a model assuming the form

$$x_i = \overline{x_i} + z_i \tag{11}$$

where: x_i is a time series of the air parameter, $\overline{x_i}$ is a non-stationary low change rate component representing changes in the average value, and z_i is a stationary, high change rate random component representing disturbances.

3.2. Statistic analysis

For the time series $\{x_i\}$, $i = 1, \ldots, n$, the basic statistic parameters are determined (Bendat, Piersol 1976; Otnes, Enochson 1978):

- Average value

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{12}$$

- Variance

$$s^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{13}$$

- Histogram, i.e. a sequence of empirical size together with the corresponding sequence of sub-ranges. Recognition of the histogram enables to formulate a hypothesis on the type of probability distribution of the time series values. For the purpose of testing of this hypothesis, that values of the time series have the specific type of distribution, one can use the Pearson's consistency test χ^2 or Kolmogorov test λ (Greń 1974).

3.3. Correlative and spectral analysis

The basic tool for correlative analysis of the time series $\{x_i\}$, $i = 1, \ldots, n$, is an estimator of the covariance or correlation function (equivalent in cases of the average value equal zero). Equation that defines covariance of time series shall be as follows (Bendat, Piersol 1976; Otnes, Enochson 1978):

$$C_k = \frac{1}{n-k} \sum_{i=1}^{n-k} (x_i - \bar{x})(x_{i+k} - \bar{x}), \qquad k = 0, 1, \ldots, n-1 \tag{14}$$

and for correlation

$$R_k = \frac{1}{n-k} \sum_{i=1}^{n-k} x_i, x_{i+k}, \qquad k = 0, 1, \ldots, n-1 \tag{15}$$

If all elements R_k of the correlation function are divided by R_0, then a normalized correlation function (autocorrelation) r_k will be obtained.

In case of two time series $\{x_i, y_i\}$, $i = 1, \ldots, n$, the equation that defines cross-covariance shall be as follows (Bendat, Piersol 1976; Otnes, Enochson 1978):

$$C_{xy}(k) = \frac{1}{n-k} \sum_{i=1}^{n-k} (x_i - \bar{x})(y_{i+k} - \bar{y}), \qquad k = 0, 1, \ldots, n-1 \tag{16}$$

and for cross-correlation

$$R_{xy}(k) = \frac{1}{n-k} \sum_{i=0}^{n-k-1} x_i , y_{i+k}, \qquad k = 0, 1, \ldots, n-1 \tag{17}$$

The basic tool for the spectral analysis of the time series $\{x_i\}$, $i = 1, \ldots, n$, is an estimator of spectral density, defined with the discrete Fourier transform of correlation R_k

$$S_k = \Delta t \sum_{i=0}^{n-1} R_i e^{-j\frac{2\pi i}{n}k}, \qquad k = 0, 1, \ldots, \frac{n}{2} - 1 \tag{18}$$

and in case of two time series $\{x_i\}$, $\{y_i\}$ for $i = 1, \ldots, n$, is an estimator of spectral inter-density defined with the discrete Fourier transform of cross-correlation $R_{xy}(k)$

$$S_{xy}(k) = \Delta t \sum_{i=0}^{n-1} R_{xy}(i) e^{-j\frac{2\pi i}{n}k}, \qquad k = 0, 1, \ldots, \frac{n}{2} - 1 \tag{19}$$

The direct method for calculating the correlation function consists in calculation according to the equation (15) and the cross-correlation function according to the equation (17). Computing of the correlation function by the basic method was extremely time-consuming, that gave justification to the necessity of developing and using the more effective and less time-consuming computing methods. Presently the methods that apply FFT procedures of quick Fourier transform are used most frequently; this is for the number of elements equal N, being integral power of the number 2. If the size n of the time series is less than 2^p, then the number of elements can be limited up to $N = 2^{p-1}$ or to assume $N = 2^r$ and to complete the time series with noughts. In order to determine the correlation function, the analysed time run has been Fourier transformed and in this way a spectrum has been obtained. To transform this spectrum, the FTF procedure has been used. Although this approach might be regarded non-direct, but the coefficient of calculation time reduction is of a considerable value (the greater is maximum delay, the greater is reduction of calculation time). This method consists of the following phases:

1) calculated is the Fourier transform X_k of time series x_i for i, $k = 0, 1, \ldots, N-1$,

2) calculated is the "non-smoothed" (i.e. without any modifications that take into consideration the finite time of analysis) estimator of spectrum $S_k = \frac{\Delta t}{N} | X_k |^2$,

3) calculated is inverted Fourier transform R_k of spectrum S_k being an estimator of correlation function.

As a result of the above method, a so-called "cyclic" function of correlation is obtained. Separation of its two overlapping parts may be achieved by supplementing the samples sequence with a sequence comprising of noughts (Otnes, Enochson 1978).

Analogous method is being applied to calculation of cross-correlation function.

Also in cases of calculation of the spectral density function, presently the Fourier transform methods, called direct methods are used most frequently. In this case:

1) calculated is Fourier transform of data $X_k = \sum_{i=0}^{N-1} x_i e^{-j\frac{2\pi i}{N}k}$, $k=0, 1, ..., N-1$,

2) the spectral density is obtained from the values calculated as in the following equation $G_k = \frac{2\Delta t}{N} |X_k|^2$, $k = 0, 1, ..., (N + 1)/2$.

The whole interval of frequency $[0,1/(2\Delta\tau)]$ is divided here into $N/2$ number of sub-intervals, thus the discrete frequencies are distanced with $\Delta f = 1/(N\Delta t)$.

The practical applications of the above methods raise two basic issues: statistic fluctuations of estimators and so-called leaking of spectrum that is caused by the finite time of data analysis and results in diffusion of spectrum. Error of the spectrum estimation using Fourier transform remains considerable. The proper reduction of error one can achieve by averaging the spectrum. All methods applied to reduce leaking of spectrum are based on modification of the orthogonal function in the domains of time or frequency. For calculation Goodman-Enochson-Otnes window (GEO) as well as the final smoothing of frequencies were applied (Otnes, Enochson 1978).

Analogous method may be applied to calculate the spectral inter-density function.

4. Registration of measuring signals in a mine

The statistic methods adopted for the process identification have such advantage, that they do not require experiments, but enable to make use of data acquired in the course of regular mining production. This propensity has been used for the analysis of mine air parameters. In the mine systems of gas measuring and ventilation monitoring, the measuring data of air are recorded currently. These data can be used for performing analysis of signals. Such analysis has been carried out for the following signals representing the parameters of the mine air:

- air pressure,
- air velocity,
- concentration of methane,
- concentration of carbon monoxide

All the above parameters have been measured automatically with stationary sensors mounted in the mine working sections in accordance with the mine industry regulations or guidelines for application of the individual sensors.

Air pressure has been measured with the air physical parameters sensor of THP-1 type. The pressure was measured in the range of 800 to 1300 hPa, with the accuracy ±10 Pa. For analysis, the signals registered in a 10 sec. cycle at two points underground, were used. One point was located in the fresh air current in proximity of downcast shaft, while the other was in proximity of upcast shaft.

Air velocity has been measured with the ultrasonic anemometer of AS-2 type, of the measurement range ±10 m/s, with the accuracy of 5%. For analysis, the signals registered at mine working in the fresh air current in proximity of downcast shaft were used (10 sec sampling).

Methane concentration has been measured with the pellistor sensors of CMI type being applied in the methane-monitoring systems. The measurement range was 0–5 % CH_4 with the accuracy of 0.1% CH_4. For analysis, the signals registered at two points of the mine production region, i.e. at the outlet of longwall C_2 and at outlet of longwall C_3 were used (240 sec sampling).

Carbon monoxide concentration has been measured with the commonly used in the early fire-detecting systems electro-chemical sensor of ACO-4B type. The measurement range was of 0-200 ppm CO, with accuracy of 2%. For analysis, the signal registered at the outlet of mine production region was used (300 sec sampling).

5. The results of signal analysis and their interpretation

5.1. Air pressure in mine workings

Barometric pressure and its disturbances have a significant impact on the deep mine ventilation conditions (Wasilewski 1998). To identify the range and dynamics of changes in barometric pressure as well as their impact on the ventilation conditions underground, the observations of pressure changes in the mine workings were carried out. The pressure signal was observed on the mine surface and in workings for over one year, whereas for detailed analysis the twenty-four hours registrations of signal were used. Registration of pressure signals was initially made every 2 sec, then in 5 sec intervals, and after including pressure sensors into the monitoring system, registration of monitoring was executed in 10 sec intervals.

The analysis of barometric pressure changes on the surface has proved that air pressure is subjected to both rapid changes of short duration as well as to slow fluctuations. The short-duration pressure changes are those observed every day. Examination of the yearly record of registrations proved that in winter seasons its course is rather slow (moderate) and rarely characterised by rapid changes, the latter are more frequently observed in spring-autumn seasons. For instance, the average velocities of pressure changes rarely exceed 1 hPa/hour, although the changes peak values may exceed even 4 hPa/hour. The long-duration pressure changes are of slow pace, the average velocities of which do not exceed 25 hPa per day, and their consequences are the seasonal fluctuations of air pressure (winter-summer). The range of such fluctuations, at the yearly average air pressure equal 998 hPa, did not exceed 10%. Simultaneous observations of the barometric pressure on the surface and underground in the mine workings have proved that the pressure changes registered underground contain the greater number of random components resulted from the local disturbances of pressure (Fig. 1).

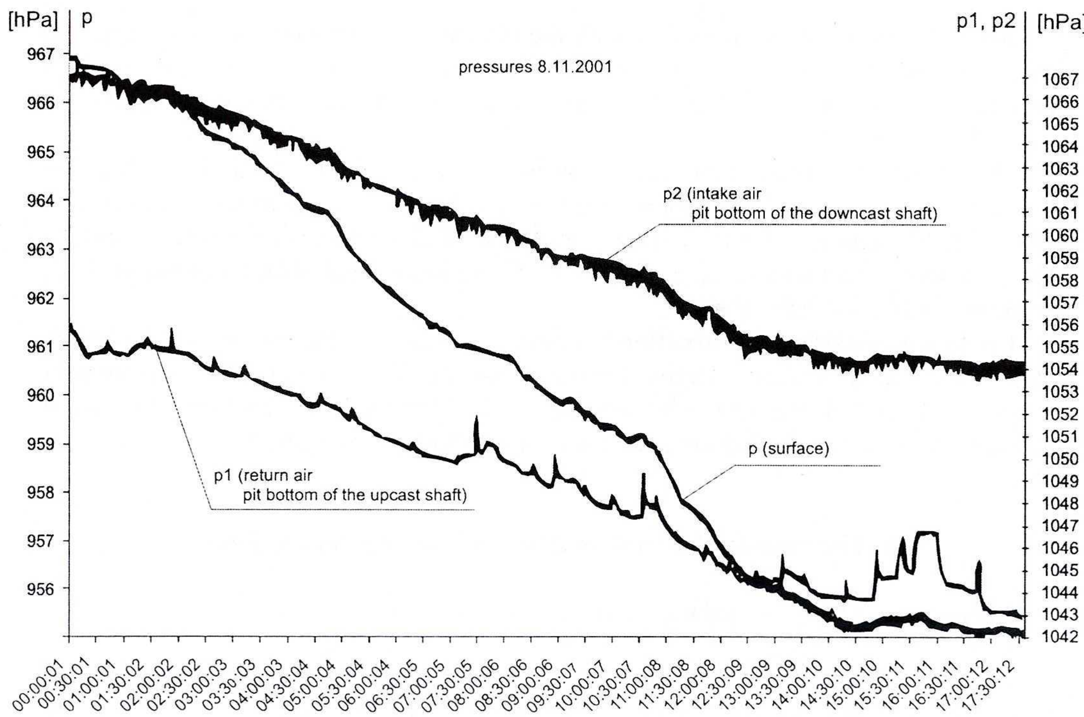


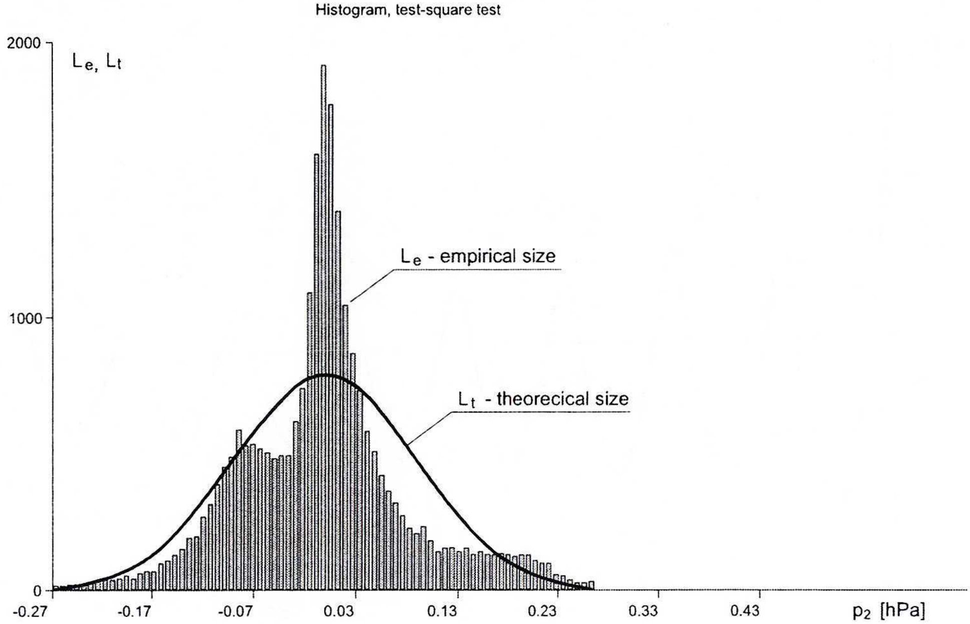
Fig. 1. Barometric pressures on the surface and in the mine workings

Rys. 1. Ciśnienia barometryczne na powierzchni oraz w wyrobiskach kopalni

The analysis of pressure in the mine workings has been performed to observe signals registered in the fresh air current at the bottom of the downcast shaft, and in the used air current in proximity of the upcast shaft. Air pressure in the underground workings follows the slow-variability fluctuations of the barometric pressure on the surface; therefore signals are generally of non-stationary character. With application of a low--pass filter of smoothing period about one week ($\alpha = 0.998$), the stationary components representing random disturbances were separated from the pressure signal. The result of a normality test for the empirical distribution of probability (Fig. 2) was, however negative for the significance levels equal 1.05 and 1%, respectively.

Normalised auto-correlation of random components has decaying course, regardless of the place of pressure observation underground. At the same time it was stated that a random component for the registered signal of the fresh air current in proximity of downcast shaft (Fig. 3) is of a strong and distinct periodicity ($T = 60$ sec). Interpretation of such pressure oscillation period requires the additional testing, in order to resolve whether this is a result of disturbances caused by the hoisting machine or of other disturbances. The spectral density estimated at the 16-element smoothing window was practically of zero value within the full frequency range.

a)



b)

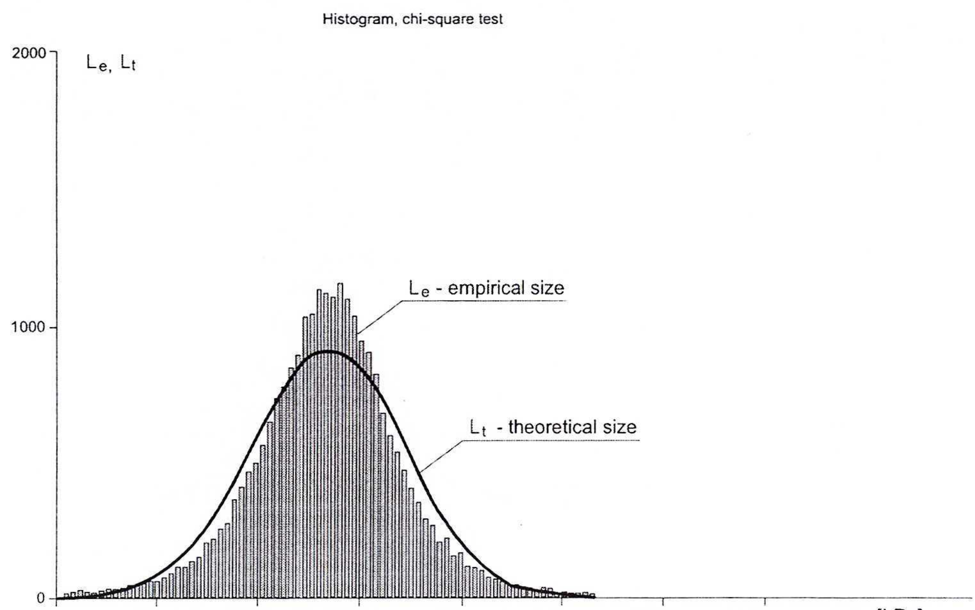


Fig. 2. Histogram of stationary components of the air pressure signal in proximity of the downcast shaft (a) and upcast shaft (b)

Rys. 2. Histogram składowych stacjonarnych sygnału ciśnienia powietrza w pobliżu szybu wlotowego (a) i wylotowego (b)

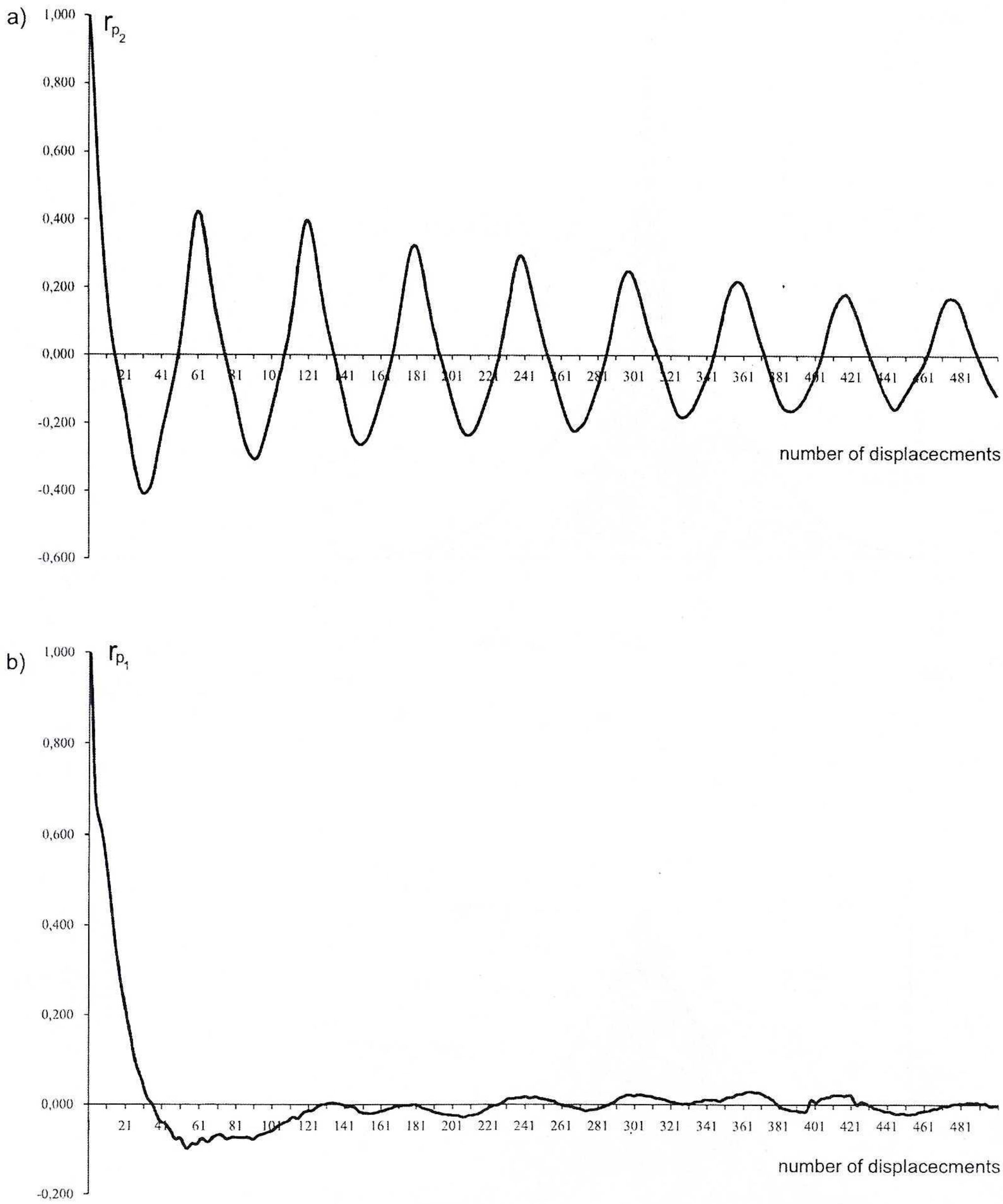


Fig. 3. Normalised auto-correlation of stationary components of air pressure registered in proximity of the downcast shaft (a) and upcast shaft (b)

Rys. 3. Autokorelacja unormowana dla składowych stacjonarnych ciśnienia powietrza rejestrowanych w pobliżu szybu wlotowego (a) i wylotowego (b)

5.2. Air velocity in a mine working

The air velocity signal of duration time about one month was observed. The signal course during a week observation was of non-stationary character. To separate the slow-variability non-stationary components from the observed air velocity signals, the low-pass filtration was applied. For the filtration coefficient within a range from 0.662 — which corresponds to smoothing period of about one hour — up to 0.998 (smoothing period of about one week) the air velocity signal division into components: non-stationary $\bar{v}(t)$ and random stationary $z_v(t)$ was achieved. For a day period of smoothing (α = 0.983) the velocity signal division (Fig. 4a) into slow-variability component (Fig. 4b) and random component (Fig. 4c) in the average value range equal 0.001 and variance 0.0255 was obtained.

For the stationary random component of air velocity the histograms of empirical distribution were determined and a normality test was performed. For a week realisation a positive result of the test of significance level 0.05 was obtained, i.e. one has no grounds to dismiss a hypothesis on the normality of empirical distribution of the air velocity random component (Fig. 5).

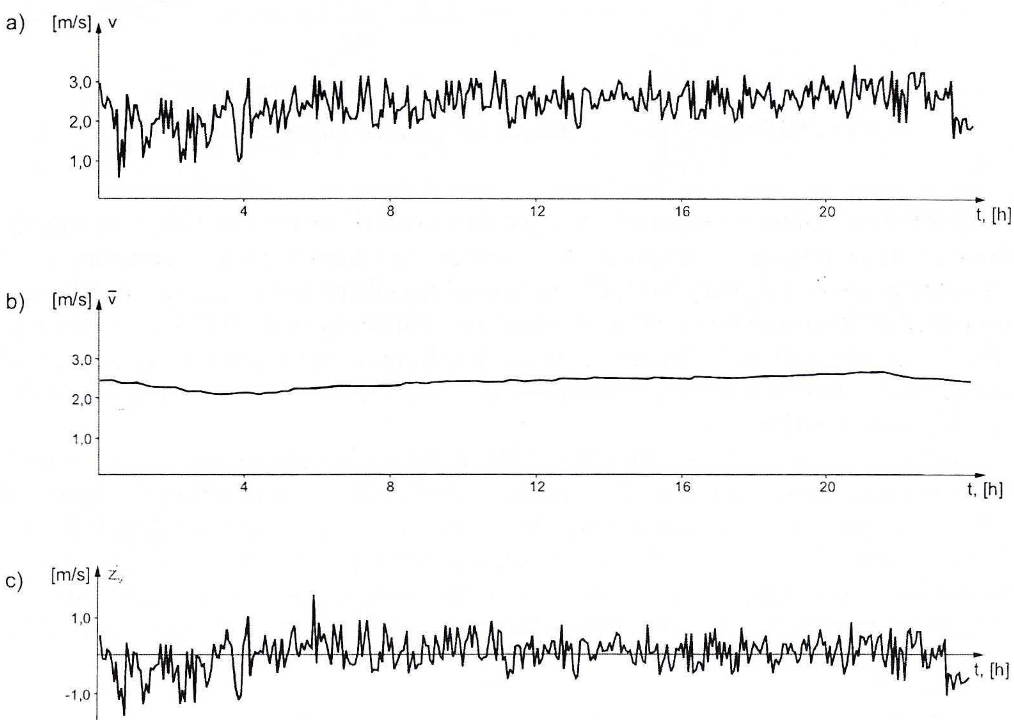


Fig. 4. Air velocity (a) and its non-stationary (b) and stationary (c) components.

Rys. 4. Prędkość powietrza (a) i jego składowe: niestacjonarna (b) i stacjonarna (c)

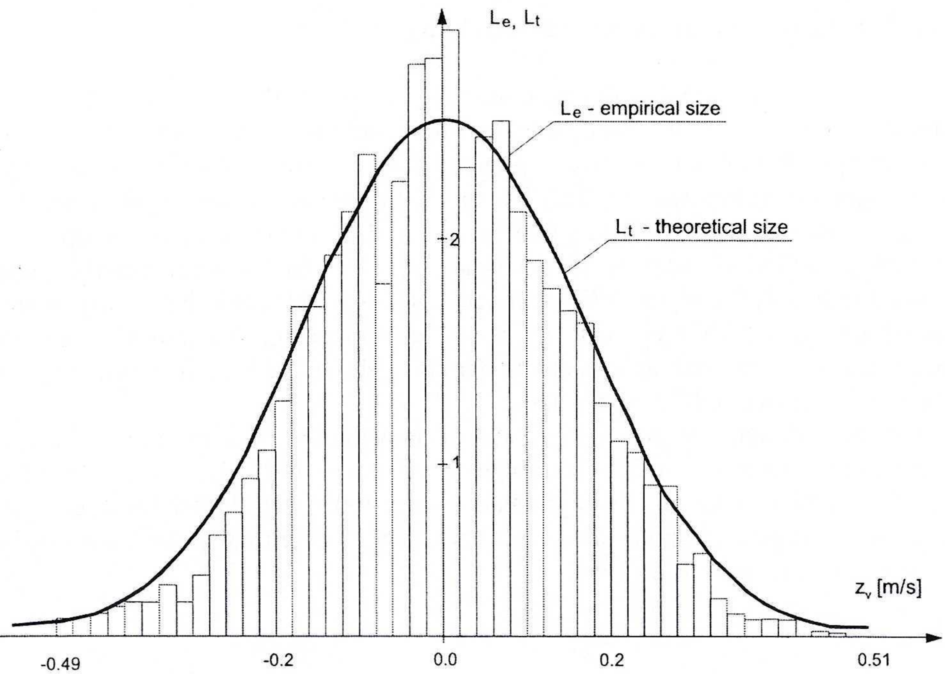


Fig. 5. Histogram of a stationary component z_v of the air velocity signal

Rys. 5. Histogram składowej stacjonarnej z_v sygnału prędkości powietrza

Normalised auto-correlation of random components of air velocity (Fig. 6) is rapidly decaying to zero value, which proves that momentary values of random components of air velocity are weakly correlated, like in case of broadband noise. The spectral density estimated at 16-element smoothing window lasts practically in the full frequency range (Fig. 7), i.e. similarly as for broadband noise. The forms of auto-correlation and spectral density indicate that a stationary component of air velocity in mine workings is the ergodic normal white noise.

Testing in mine workings (Wasilewski 1996), where air velocity was measured with various anemometers, and sampling periods were differentiated within the range of 0.5–20 sec, proved that the auto-correlation function for the air velocity signals decays down to zero value for $\Delta\tau = 10$ sec regardless of the type of anemometer. It was also proved that such considerable randomness of the velocity signal is a result of impact of the air turbulence component that in the monitoring systems may be smoothed by digital filtration methods.

5.3. Methane concentration in the mine production region

Testing of methane concentration signals was performed (Wasilewski 1986) for a month observation of signals registered at the outlet of longwall $C_2(t)$ and at the outlet

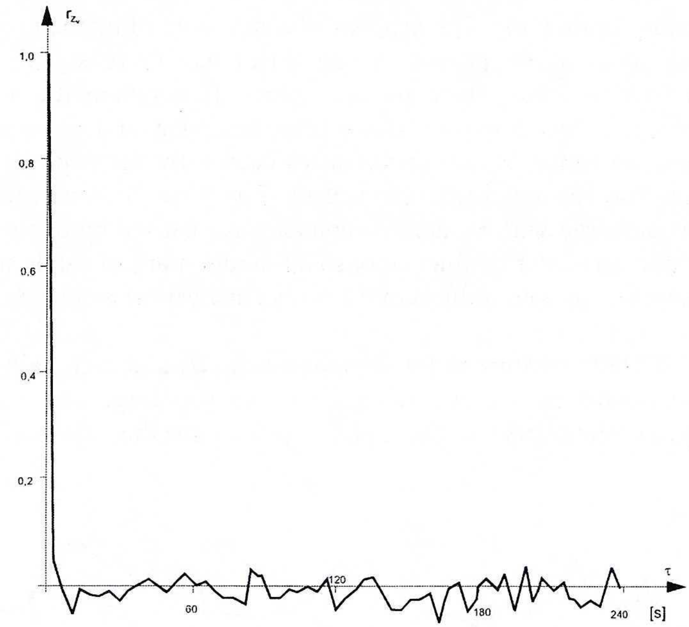


Fig. 6. Normalised auto-correlation of a stationary component z_v of the air velocity signal

Rys. 6. Autokorelacja unormowana składowej stacjonarnej z_v sygnału prędkości powietrza

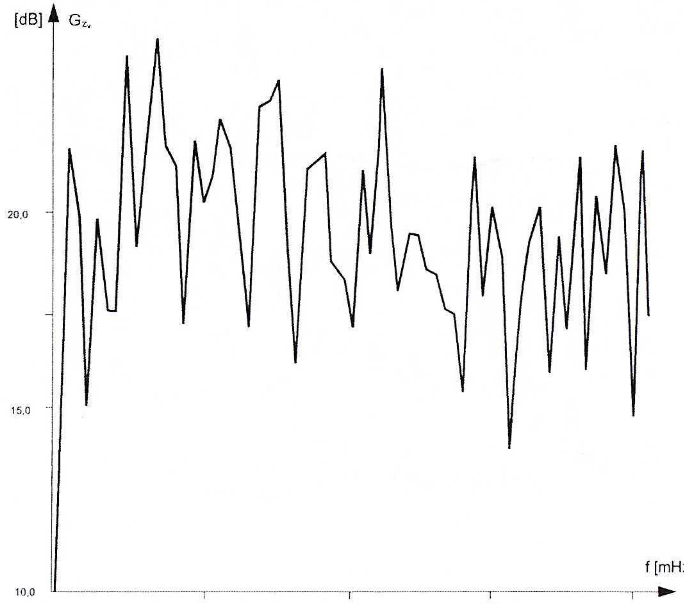


Fig. 7. Spectral density of a stationary component z_v of the air velocity signal

Rys. 7. Gęstość widmowa składowej stacjonarnej z_v sygnału prędkości powietrza of mine production region $C_3(t)$. The analysis of stationarity of methane concentration signals for week observations proved in both cases that those signals are of non--stationary character regarding their average values. Eliminating the non-stationary average value of signals by a low-pass Brown filter method, a random component $z_C(t)$, representing methane concentration disturbances caused by the exploitation in mine production region was separated from the signals (Fig. 8 and 9). One can assume that disturbances characterised with random components are caused by exploitation work, but their amplitude, character of fluctuations and duration are of random nature. Just those random components were subject of the further analysis of methane concentration signals.

The stationarity tests performed for components $z_{C_2}(t)$ and $z_{C_3}(t)$ allowed to consider those components as stationary, regarding their average and square values. Statistical analysis of stationary components $z_C(t)$ proved that the stationary components

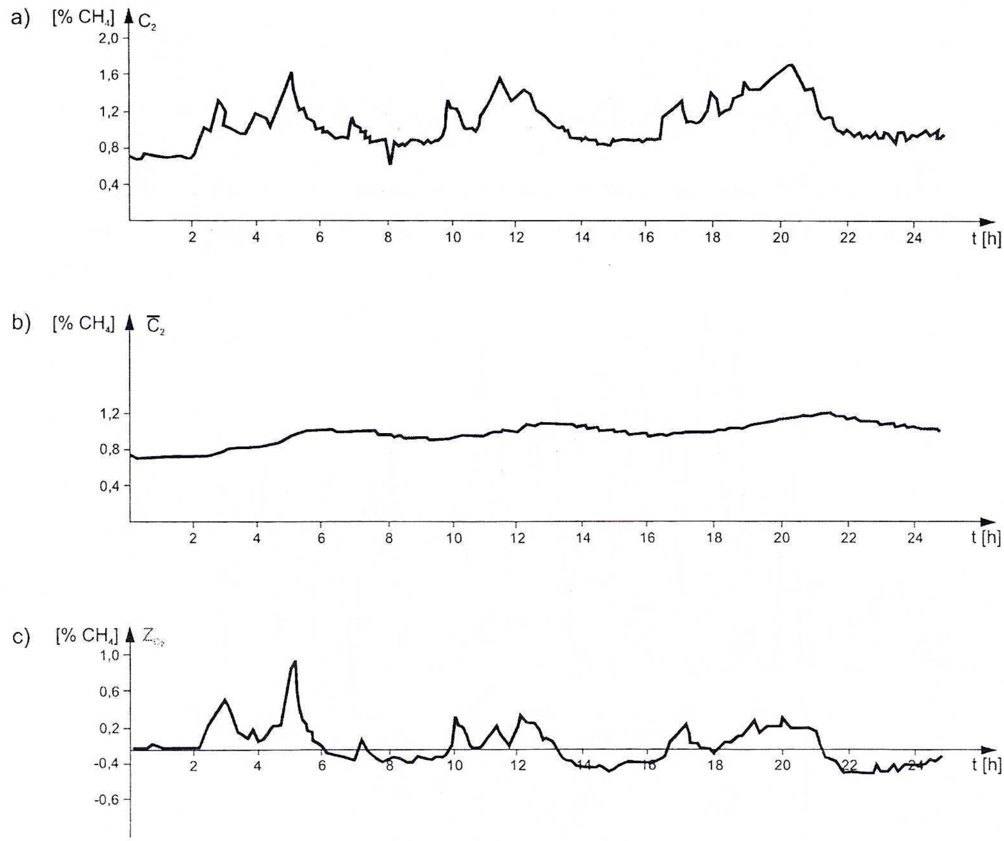


Fig. 8. Methane concentration at the outlet of longwall $C_2(t)$ (a) and its non-stationary (b) and stationary (c) components

Rys. 8. Stężenie metanu na wylocie ze ściany $C_2(t)$ (a) i jego składowe: niestacjonarna (b) i stacjonarna (c)

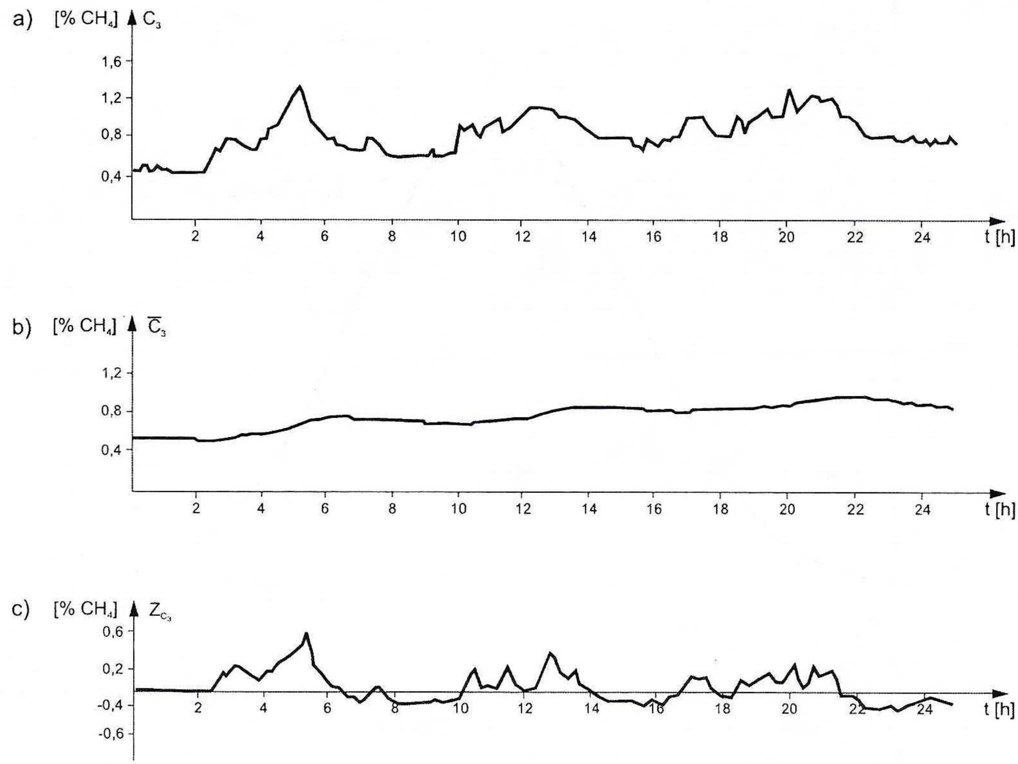


Fig. 9. Methane concentration at the outlet of region $C_3(t)$ (a) and its non-stationary (b) and stationary (c) components

Rys. 9. Stężenie metanu na wylocie z rejonu $C_3(t)$ (a) i jego składowe: niestacjonarna (b) i stacjonarna (c)

of the methane concentration signal at the outlet of longwall were of greater intensity and variability than random components of methane concentration signal measured at the region outlet. This was just what was expected, since methane concentration sensor

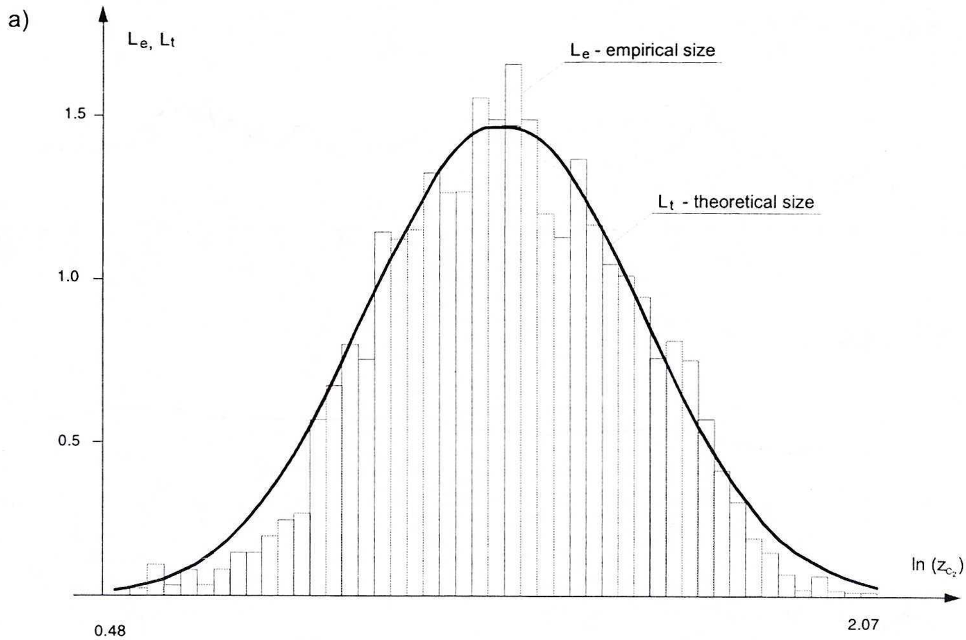
TABLE 1

Statistic parameters of stationary components of methane concentration signals

TABLICA 1

Parametry statystyczne składowych stacjonarnych sygnałów stężenia metanu

Signal	Average value	Minimum value	Maximum value	Range	Standard deviations
Z_{C2}	0.013	–0.787	0.975	1.762	0.170
Z_{C3}	0.009	–0.726	1.102	1.828	0.132



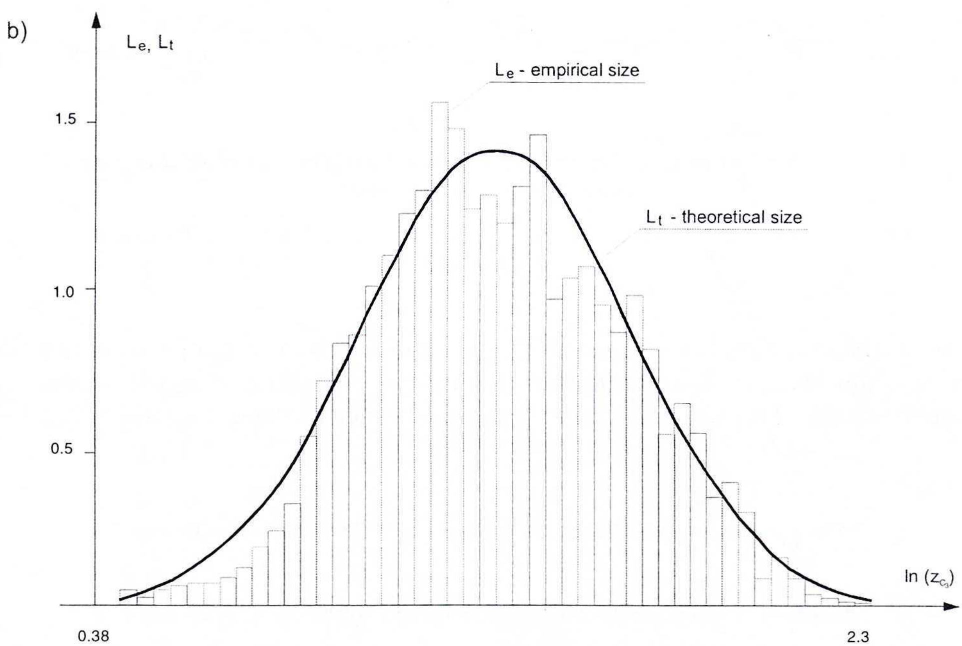


Fig. 10. Histogram of stationary components of methane concentration signal at the outlet of longwall z_{C_2} (a) and at the outlet of region z_{C_3} (b)

Rys. 10. Histogram składowych stacjonarnych sygnału stężenia metanu na wylocie ze ściany z_{C_2} (a) oraz na wylocie z rejonu z_{C_3} (b) at the region outlet is located in longer distance from the disturbance source (longwall) and amplitude of disturbances is affected by the natural smoothing caused by a better mixing of methane and air during of mixture flow in the top road. Some statistical parameters of random components of methane concentration signals are shown in Table 1.

The determined histograms of disturbances $z_{C_2}(t)$ and $z_{C_3}(t)$ are not consistent with the probability density of normal distribution, which was proved on the basis of distribution consistency tests. In both cases a similarity of histograms to the probability density of logarithmic-normal distribution (Fig. 10) was observed.

Auto-correlations of the stationary components of methane concentration signals $z_{C_2}(t)$ and $z_{C_3}(t)$ for week realisations are of distinctly periodic al character and are similar to a co-sinusoid of decaying amplitude (Fig. 11), of period equal about 8 h (process shift). This proves that methane concentration signals transfer the periodicity of shift-cycle of the process.

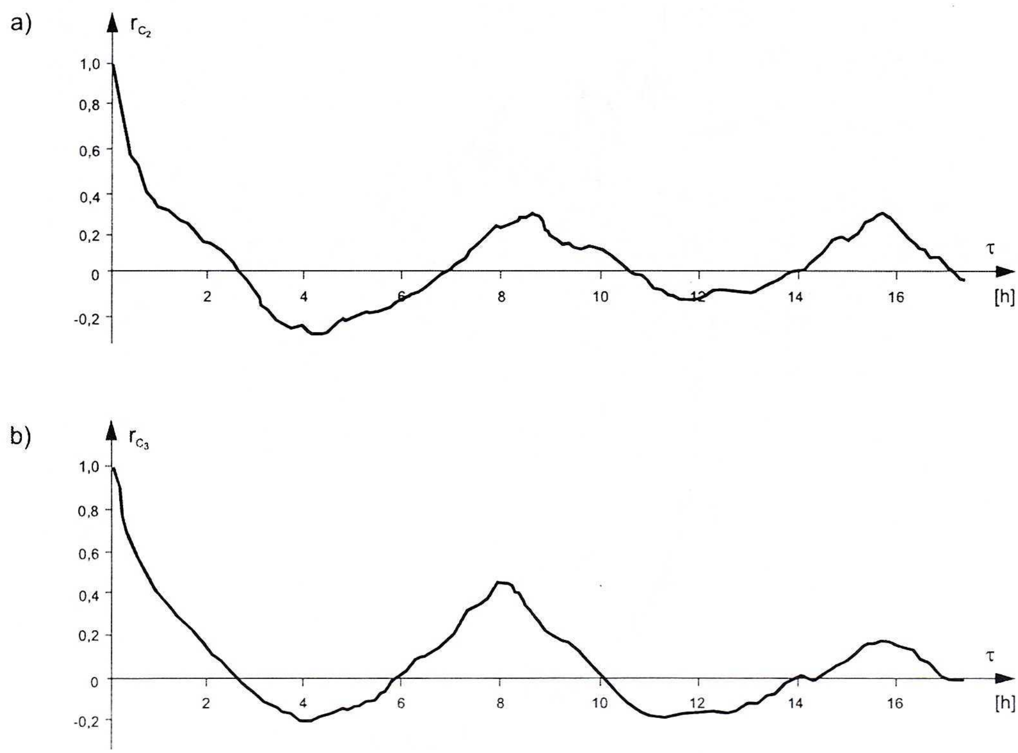


Fig. 11. Normalised auto-correlation of stationary components of methane concentration signal at the outlet of longwall z_{C_2} (a) and at the outlet of region z_{C_3} (b)

Rys. 11. Autokorelacja unormowana składowych stacjonarnych sygnału stężenia metanu na wylocie ze ściany z_{C_2} (a) oraz wylocie z rejonu z_{C_3} (b)

Confirmation of this observation is occurrence of the function maximum of methane concentration spectral density random components for frequency corresponding to duration of a single process shift. The course of spectral density function (Fig. 12) confirms the previous statement on the greater variability of a signal at the longwall outlet and — partial smoothing of a signal at the region outlet. The spectral density of random component of methane concentration decays more rapidly within the high--frequency range.

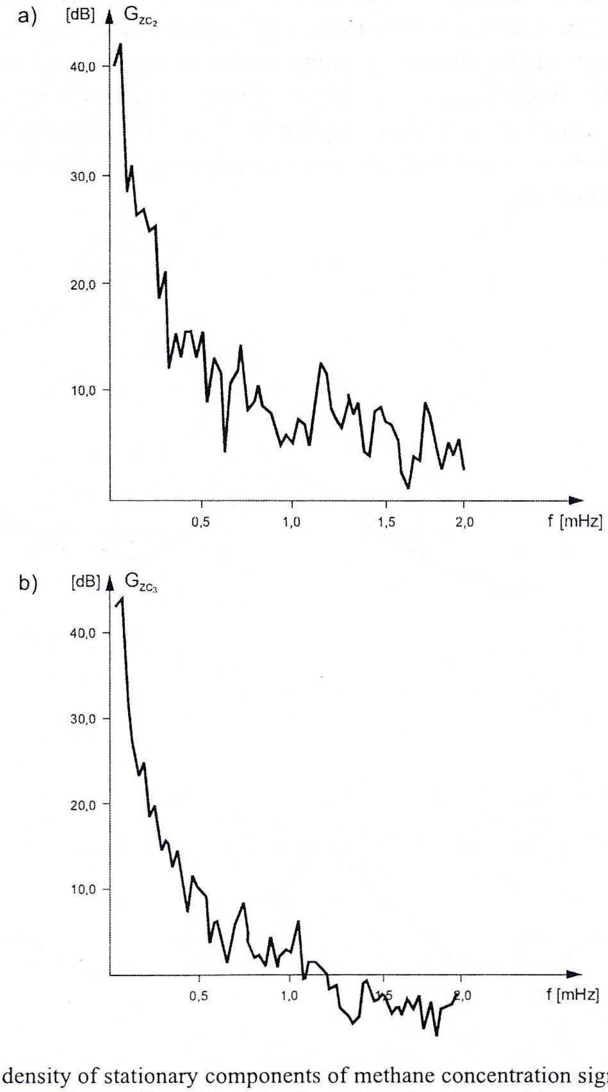


Fig. 12. Spectral density of stationary components of methane concentration signal at the outlet of longwall z_{C_2} (a) and at the outlet of region z_{C_3} (b)

Rys. 12. Gęstość widmowa składowych stacjonarnych sygnału stężenia metanu na wylocie ze ściany z_{C_2} (a) oraz wylocie z rejonu z_{C_3} (b)

5.4. Carbon monoxide concentration in mine air

Underground fires are the most serious hazards occurring in the deep coal mines. The long-years observations have proved that automatic measurements of carbon monoxide concentration, performed frequently and appropriately processed, are practically sufficient for fire detecting in the mine workings (Krzystanek, Szywacz, Wasilewski 1984). Numerous disturbances occurring in the ventilation system as well as random or technological fluctuations of carbon monoxide concentration in mine air may considerably impede the correct interpretation of reasons for changes of a measurement signal. Among the most troublesome disturbances (Szywacz 2001) are changes in air flow, carbon monoxide emission at shooting, and fluctuations of carbon monoxide concentration in the uptake air. It is especially difficult to analyse measuring signal disturbances caused by shooting, because the shape of carbon monoxide concentration changes is very similar to the shape of carbon monoxide concentration changes at the initial phase of underground fire.

The preliminary analysis of measuring signal of carbon monoxide concentration was performed for about a dozen measuring series registered during the carbon monoxide analysers testing in one of the coal mines (Szywacz 2001). As a result of this analysis, it was stated as follows:

- On the basis of correlation and spectral analysis it was determined that the frequency bands of carbon monoxide concentration signals can be limited with frequency f_g = 1.5 mHz. Applying the Kotielnikow-Shannon theorem on sampling, one can estimate the maximum sampling period as near 5 minutes.
- The signal disturbances are of slow-variability character, of frequencies lesser than 0.2 mHz, which corresponds to components of duration measured in hours and longer. This means that disturbances may occur in the same frequency band as a useful component.
- Amplitude of disturbances was about 0.002%, whereas in case of exogenous fire it reached 0.006%.
- Observation of disturbances after shooting and their incremental examination proved that in all disturbances of this type local maxima and points of inflection occurred, where a point of inflection occurred after about 20 minutes, and the first maximum about 20–40 minutes. In case of exogenous fire signal recording, the continuous increment of signal throughout about 100 minutes was observed.

Analysis of the carbon monoxide concentration signal commenced with elimination of rapid peaks occurring in the signal that resulted from shooting or scaling of the analyser. Those disturbances were considered as determined and not bearing any information on the character of changes of carbon monoxide concentration signal. Because during observation, the increased emission of carbon monoxide, arising from developing spontaneous combustion of coal, did not occur; it was recognised that the carbon monoxide concentration signal changes (Fig. 13) were caused only by natural disturbances. Therefore, from the carbon monoxide concentration signal the non-stationary slow-variation component $CO(t)$ (Fig. 13b) and random component $z_{CO}(t)$ (Fig. 13c)

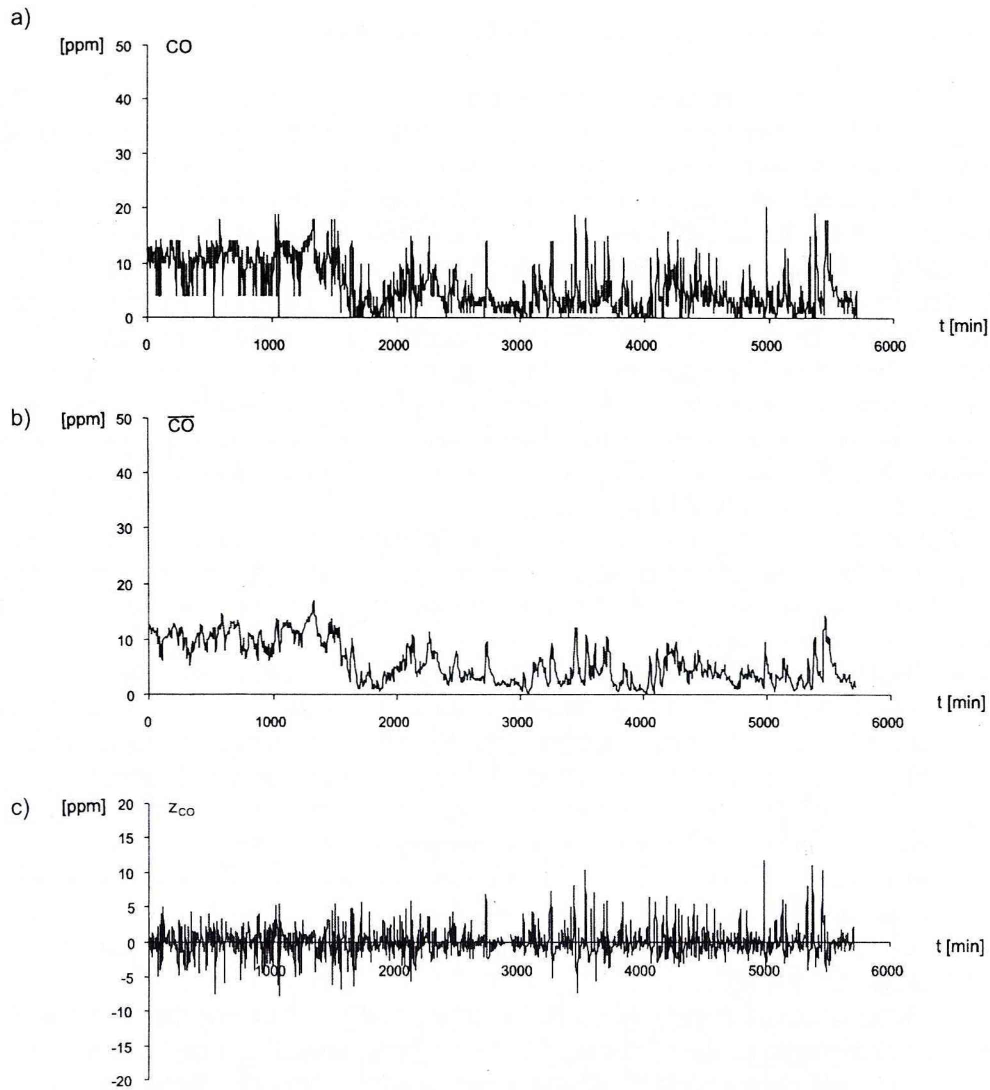


Fig. 13. Carbon monoxide concentration (a) and its non-stationary (b) and stationary (c) components

Rys. 13. Stężenie tlenku węgla CO (a) i jego składowe: niestacjonarna (b) i stacjonarna (c)

were separated. The latter was subjected to further analysis. The signal distribution into components was executed by the low-pass Brown filter for filtration coefficient $\alpha = 0.355$. Obtained component $z_{CO}(t)$ was considered stationary on the base of the series test for significance level of 0.05.

The tests χ and χ^2 on normality of probability distribution brought negative results, but the achieved histogram of empirical size was very near to theoretical sizes for a normal distribution (Fig. 14).

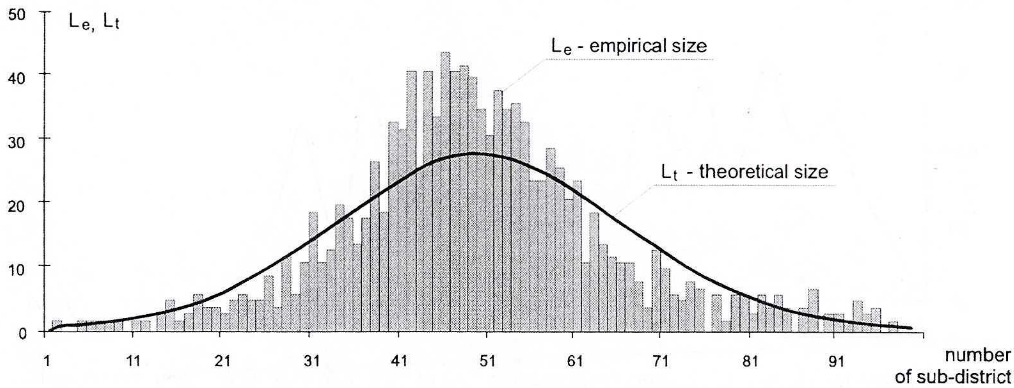


Fig. 14. Histogram of a stationary component Z_{CO} of carbon monoxide concentration signal

Rys. 14. Histogram składowej stacjonarnej Z_{CO} sygnału stężenia tlenku węgla

The auto-correlation estimator of the normalised stationary component obtained by a method of quick Fourier transform is presented in Fig. 15. It is noticeable that correlation is decaying rapidly — exponentially (is practically zero for a 5-minute displacement; a single period of sampling).

The spectral density estimator of stationary component obtained by a method of quick Fourier transform at 32-element smoothing window is presented in Fig. 16. It is noticeable that spectral density is practically constant within the full transmission range equal 1.667 mHz.

The forms of histogram, auto-correlation and spectral density suggest that the stationary component of carbon monoxide concentration in mine air is the ergodic normal white noise.

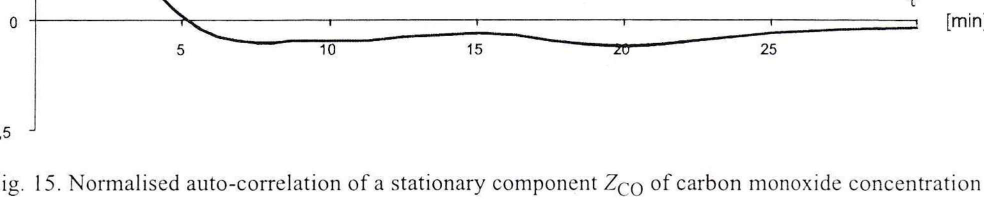


Fig. 15. Normalised auto-correlation of a stationary component Z_{CO} of carbon monoxide concentration signal

Rys. 15. Autokorelacja unormowana składowej stacjonarnej Z_{CO} stężenia tlenku węgla

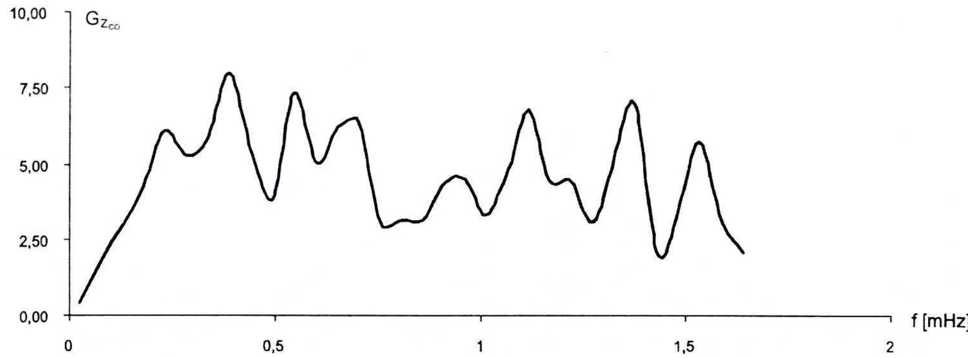


Fig. 16. Spectral density of a stationary component Z_{CO} of carbon monoxide concentration signal

Rys. 16. Gęstość widmowa składowej stacjonarnej Z_{CO} stężenia tlenku węgla

6. Examples of analysis application in monitoring and control systems

6.1. Correlative methods for the disturbance propagation tests

Technological activities in the mine production regions, in particular shooting or welding, cause numerous disturbances of gas concentration that move pursuant to the air flow direction. These disturbances, registered in the monitoring system, were used as the "natural tracer gases" for determination the real time and velocity of disturbances dislocation in the underground workings network (Wasilewski 1998). In computer monitoring systems, the current and automatic determination of these parameters is possible. Identification of real times of smokiness may be of a great significance for the actions of rescuing the staff in case of fire.

Determination of a transport delay time

Transport delays of gas disturbances, i.e. times of disturbances propagation in the ventilation system are observed when a post-shooting curve of methane or carbon monoxide concentration is registered at the consecutive measuring points along the way of air flow towards upcast shaft. Disturbance propagation time may be determined directly or by using the cross-correlation function (Wasilewski 1998). The transport delay time is being determined from cross-correlation function as a displacement τ corresponding to the maximum value of cross-correlation function of these signals ($t_o = \tau_{max}$).

The values of transport delay times of the carbon monoxide disturbance signals propagation in the region of longwalls 92 and 93 at the Miechowice coal mine (Fig. 17) were determined on the basis of observation of carbon monoxide concentration after shock-shooting during drift driving No. 64. Carbon monoxide concentrations were

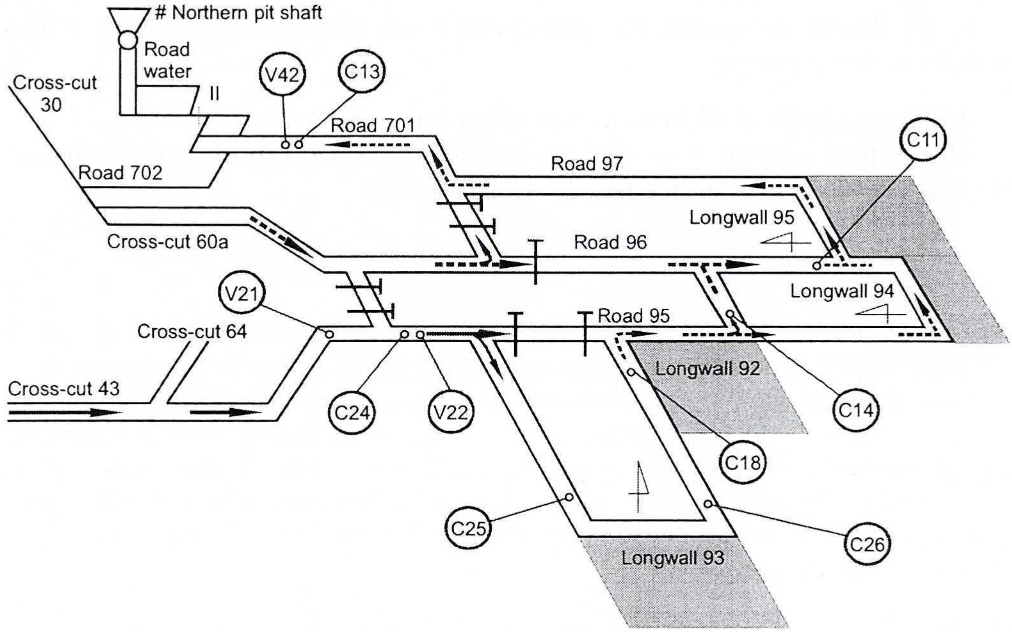


Fig. 17. Scheme of the shooting observation region in seam No. 509 KWK Miechowice

Rys. 17. Schemat rejonu obserwacji strzelań w pokładzie 509 KWK Miechowice

measured respectively by sensors C24, C18, C14, C11 and C13. Propagation of carbon monoxide disturbances after shock-shooting is presented in Figure 18. The carry times of transport delay were estimated by a method of cross-correlation function and were given in Table 2, where delays were given in seconds (above a diagonal), and distance between measuring points — in metres (under the main diagonal).

TABLE 2

Time of transport delays for carbon monoxide concentration after shooting

TABLICA 2

Czasy opóźnień transportowych dla stężenia tlenku węgla po strzelaniu

Time [sek] / Distance [m]	C24	C18	C14	C11	C13
C24		740	840	980	1 400
C18	500		100	240	660
C14	720	220		140	560
C11	1 000	500	280		420
C13	1 650	1150	930	650	

So the determined disturbances propagation times show strong structural relation with the sensors network.

Average velocity of disturbances propagation

The average velocity of air in mine workings along the way of gas disturbances propagation can be also determined from a relationship

$$v_{sr} = \frac{L}{\tau_{max}}$$

where: L is a distance between measuring points and τ_{max} time displacement, for which the correlation function of signals registered at this point approaches its maximum.

Thus the function of signals cross-correlation may be applied for determination of average velocity, for instance at places where direct measurement is of lesser reliability, e.g. in longwalls or workings with difficult access or clamped ones, and even in abandoned workings (cavings). Using the times of carbon monoxide propagation after shooting, the average velocity of air in longwall No. 93 (Fig. 17), which was equal $v_{av} = 0.67$ m/s was calculated.

6.2. Determination of the impact of parameters on methane emission in the region

The cross-correlation function was used (Wasilewski 1986) to verify the mathematical models of ventilation process, in particular for testing how various factors affect methane emission in the region of longwall with extended cavings. It was stated that in description of those phenomena one cannot disregard the time factor. It was observed that changes in air flow, barometric pressure and also negative pressure in degassing pipeline system may cause long-hour transient state processes of methane concentration and the maximum impact of those changes may occur even after a few dozen hours. The correlation analysis of signals proved the thesis formulated in literature on the dependency of methane emission in the mine production region upon numerous parameters. The low-variability component of methane concentration at the region outlet is negatively correlated with air velocity, barometric pressure and negative pressure in degassing pipeline and is positively correlated with the signal of shift production. The transient state processes of methane concentration are long-lasting and exceed several times the duration of disturbances.

Cross-correlation $\hat{R}_{\bar{p},\bar{c}3}(\tau)$ between a low-variability component of methane concentration and barometric pressure is presented in Figure 19. This correlation is also negative and its module approaches its maximum after approximately 30 hours. Such displacement in time of the correlation function maximum that corresponds to a time delay, one can explain with progressive change of methane emission from fissures and cavities in cavings, resulting from the disturbance of pressure equilibrium (Wasilewski 1998). In case of pressure drops, the volume of methane, being released from cavings, increases progressively as increases the methane discharge from more and more distant parts of cavings. Duration of this effect depends on the capacity of mine cavings.

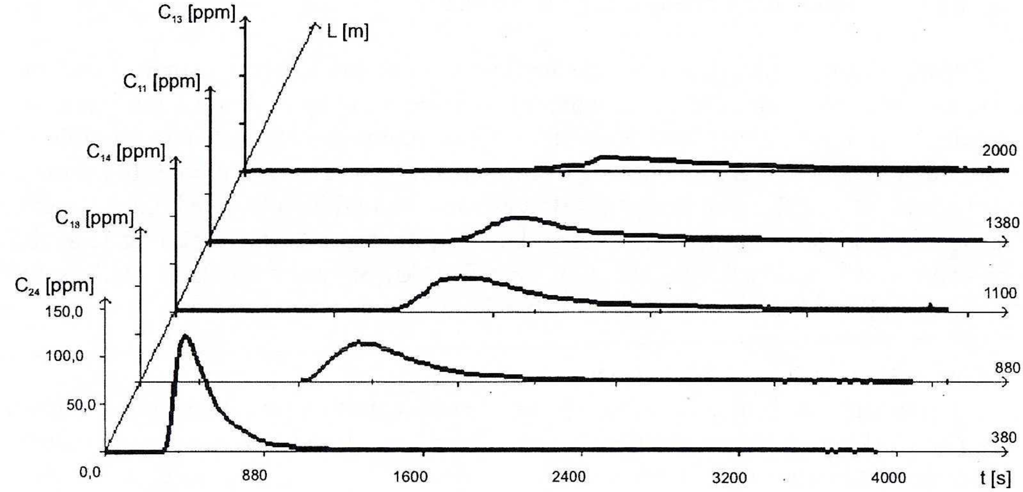


Fig. 18. Propagation of carbon monoxide disturbances in the mine ventilation system after shooting

Rys. 18. Propagacja zakłóceń tlenku węgla w sieci wentylacyjnej kopalni po strzelaniu

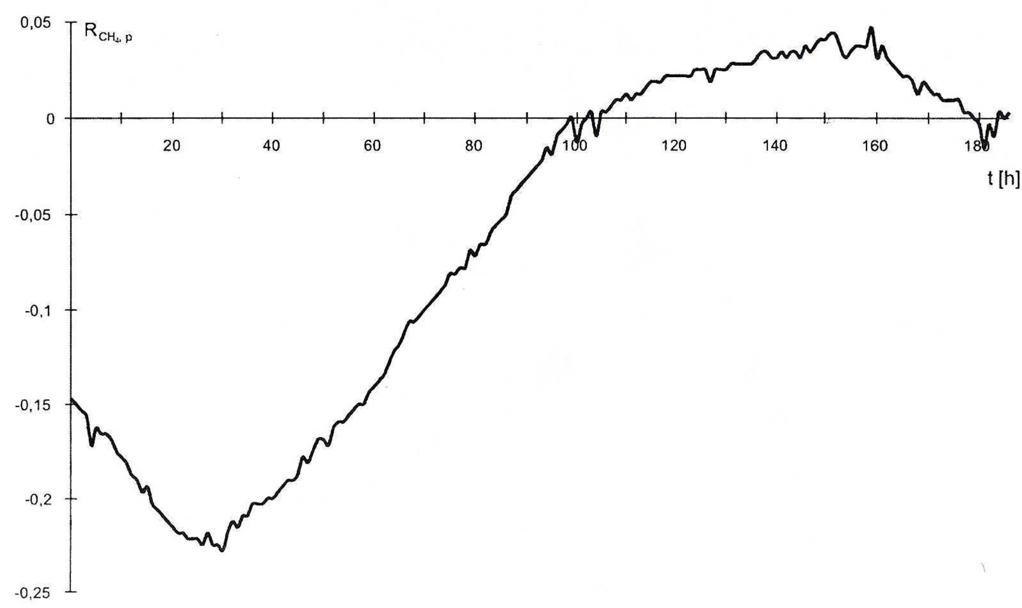


Fig. 19. Cross-correlation of methane concentration and barometric pressure

Rys. 19. Korelacja wzajemna stężenia metanu i ciśnienia barometrycznego

6.3. Estimation of released gas volume

Knowing at the same time both the air flow volume (air average velocity) and gas concentration (methane, carbon monoxide), it is possible to determine the gas concentration. In case of such events as shooting or methane breakout it is possible to estimate the volume of gas that has been released during this event. In order to estimate this volume of gas, the changes of gas flow volume should be integrated during event. Recognition of gas volume is of a considerable importance for controlling, e.g. the explosive consumption during shooting (Wasilewski, Szywacz 2002) as well as for estimation of the disaster size in case of breakout.

Gas volume released at shooting

If $C(t)$ means the course of carbon monoxide concentration [ppm] registered in time T in the working of section area equal A [m^2], and $v(t)$ [m/s] is the average velocity registered at the same time in the working, then

$$Q(t) = 0.06\,A\,C(t)\,v(t)$$

where $Q(t)$ is the course of the observed gas flow volume in l/min. For example, the diagram of carbon monoxide flow volume released during shock-shooting in cross--heading No. 64 at the Miechowice coal mine is shown in Fig. 20. Hence, the volume of this gas V_{CO} in time T expressed in litres is given with a relationship

$$V_{CO} = \int_0^T Q_{CO}(t)dt$$

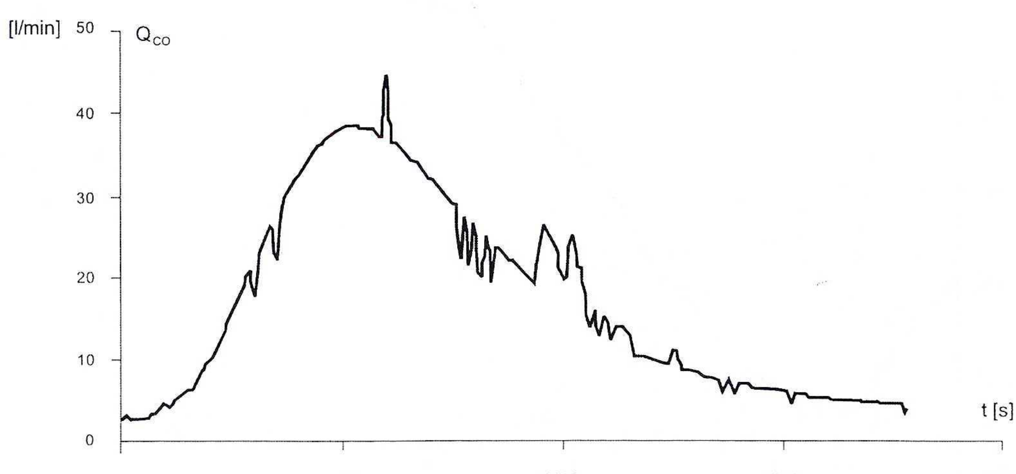


Fig. 20. Calculated quantity of carbon monoxide

Rys. 20. Obliczony wydatek tlenku węgla podczas strzelania

Volume of methane ejected into a road after explosion

To estimate volume of methane that has been ejected into the road after methane explosion that happened in the Rydułtowy coal mine in March 2002, registration of methane concentration on a sensor mounted in the region of longwall outlet was used (Report of the Commission WUG, 2002).

Assuming the air flow volume in the road as Q = 1200 m^3/min and integrating field under the methane concentration curve for the methane sensor mounted in the top road (outlet) (Fig. 21), the volume of methane being released additionally as a result of event, as Q_{CH_4} = 71.2 m^3 was obtained.

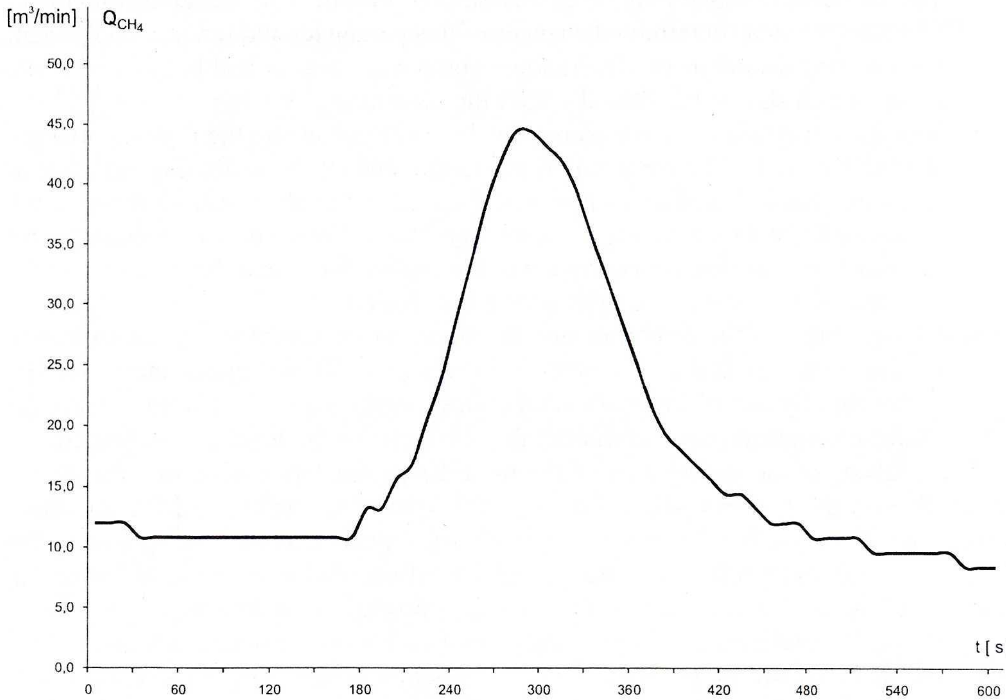


Fig. 21. Calculated quantity of methane concentration ejected into the road 10-W1 seam 703/1 Coal Mine Rydułtowy after explosion

Rys. 21. Obliczony wydatek stężenia metanu wypchnięty do chodnika 10-W1 pokł. 703/1 w KWK Rydułtowy po wybuchu

7. Conclusions

The presented above analysis of selected stochastic signals approximates the characteristics of the mine ventilation process and disturbances structure of its parameters. Realisation of such analysis is necessary to adapt the effective methods and algorithms for disturbances elimination, as well as to obtain information, essential for the ventilation process monitoring.

Summarising the results of signals analysis, one can formulate the following conclusions:

- Pressure signals registered in the mine workings are subjected to considerably slow-pace changes and follow up the barometric pressure fluctuations on the surface. Numerous disturbances of short duration are of local character and pressure registered in proximity of intake shaft shows distinct and regular oscillations.
- The air velocity signal may be expressed in a form of slow-variable component representing some determined changes of this parameter and random component representing disturbances. The random component is a normal broadband white noise, which should be filtered within the monitoring systems.
- Signals of methane concentration at the longwall outlet and the region outlet are intensely disturbed by the phenomena dependable on the technological cycle at longwall. These disturbances have not a significant impact on the slow-variable components, and their average value is equal zero. For its better mixing with air the signal of methane concentration at the region outlet may better characterise the state of methane in the mine production region.
- Changeability of the carbon monoxide concentration signal at the non-existence of fire hazard is caused by natural disturbances. These disturbances may be eliminated by use of low-pass filters which enables to select from signals the useful components (slow-variable) that characterise the level of fire hazard.

The analysis of measuring data of the mine air parameters enable to enhance the knowledge on the frequency-time nature of the tested time series, and the presented mathematical scheme for the analysis of stochastic signals may also be applied to the analyses of signals representing other parameters of ventilation process, and which in future shall be measured automatically. It is also possible to utilise these methods to analyse signals representing other physical quantities. More extensive application of the presented methods will be possible as the introduction of the measuring stations with data recording on the computer data media follows.

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