



The Analysis of Parameters Affecting Indoor Air Pollution and Noise Levels Under the Applied Theory of Covariance Functions

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Abstract: Analysis variations in the intensity of vectors estimating indoor air pollution (PM_{2.5}, PM₁₀ and CO₂) and noise levels are presented. The research was conducted in an office room during COVID-19. The theory of covariance functions was used to analyse changes in the intensity of the vectors of determined parameters. The estimates of the cross-covariance functions of digital vectors and the autocovariance functions of the individual vectors of air pollution and noise recording sensor parameters were calculated in line with the random functions of data arrays measuring the vectors of air pollution sensor parameters. The approximations of covariance functions were calculated by changing the quantisation interval on a time scale and applying software created based on the *Matlab* procedure package. The stochastic interdependence of the vectors of air pollution and noise level recording sensor parameters and variations in vectors on the time scale was established.

Keywords: indoor air pollutants, PM_{2.5}, PM₁₀, CO₂, noise level, covariance function, COVID-19

1. Introduction

Indoor air quality (IAQ) is becoming an increasingly important issue for occupational and public health (Dumale & Dudzińska 2013). The progress of civilisation forced a change in human behaviour and activity, which translated into the increased period spent indoors during the day by the inhabitants of developed countries (Staszowska 2020).

Internal air is a multiphase mixture of ingredients (gases and vapours and liquid & solid suspended substances) that surrounds humans in enclosed spaces (Maliszewska et al. 2019). A gradual increase in air pollution and environmental noise levels has rising negative effects on human health, which becomes a growing challenge under strict EU legal requirements. Around 20% of employees feel unwell due to their surroundings further deteriorating from the natural environment. Air pollution and noise levels boost along with the intensive use of transport and other factors, while the effects of air pollution on the human body depend on the nature and concentrations of pollutants in the air, the individual sensitivity of each person, the duration of pollutant exposure, etc. Foreign scientists investigated the concentrations of various pollutants like PM_{2.5}, PM₁₀, CO₂, etc. in the air of workplaces (Brace et al. 2014, Salama & Berekaa 2016, Serafimova et al. 2015, Higashikubo et al. 2017, Brdarić et al. 2019, Kolarik et al. 2015, Traumann & Tint 2014, Kogianni et al. 2020, Heberle et al. 2019, Liu et al. 2017, Canha et al. 2016, Madureira et al. 2015, Zorpas & Skouroupatis 2016, Pitarma et al. 2017, Rivas et al. 2014, Jung et al. 2015). The data obtained directly from sensors are analysed and assessed using specific software. Users are involved in the process of creating and analysing the information cycle. Both designers and consumers can successfully employ the BIM system.

Air pollutants may cause various human diseases such as asthma, emphysema, bronchitis, cardiovascular diseases, cancer, etc.; thus, it is very important to control the concentrations of these pollutants in indoor air. A relatively light noise of approximately 60 dB may cause headaches, dizziness, and tinnitus because the load on the human circulatory system is much higher than that under normal conditions. Research indicates that noise levels of around 42 dB may initiate sleep disturbances, leading to insomnia in the long run. The degree of noise pathology is subject primarily to noise intensity and the duration of exposure. Under the influence of noise, physical and mental working capacity is reduced by 10-25%, which deteriorates the speed of sensorimotor reactions of human hearing and vision, vibration sensitivity, and motion coordination and increases the risk of industrial injuries.



A crucial point is ensuring quality conditions indoors by establishing control over air pollutant concentrations. To decrease the concentrations of the above-mentioned air pollutants and to reduce negative effects on human health, efficient air treatment equipment is required.

As for the office air, the sources of particulate matter (PM_{2.5} and PM₁₀) may include ambient air pollution, including transport, fires (grass, forests, peatlands), poorly maintained streets in spring and summer, industry, energy facilities, houses burning biofuels during the cold season, the situations when pollutants enter the interior through leaky building structures or ventilation systems, indoor air pollution sources such as office equipment (copiers, printers), carpets, human activities, tobacco smoke, etc. The main sources of particulate matter in the office are road transport and indoor activities.

The sources of carbon dioxide in the office may embrace ambient air pollution, such as transport, industry, energy facilities, houses burning biofuels in the cold season, and the cases when pollutants enter inside through leaky building structures or ventilation systems. The sources of indoor air pollution in the office space are employees exhaling and plants emitting carbon dioxide at night. Humans exhale around 20 l of CO₂/h (Gritzki, & Rösler 2013). The evaluation of the office space volume allows for the estimation of the time when CO₂ concentration in the room air may exceed the permissible limit value, when no ventilation is installed, or when windows and doors are closed. Employees and ambient air are the main sources of CO₂ in the office.

Indoor noise levels of the buildings situated next to busy streets depend on the number of vehicles, the percentage of lorries involved in traffic, driving speed, the type of fuel used, fuel consumption, the average age of vehicles (fuel emissions comply with different Euro standards), technical condition, road surface, the level of vegetation and atmospheric meteorological conditions, including temperature, relative humidity, wind speed and direction and atmospheric pressure. The acoustic characteristics of the building elements embracing the noise levels of engineering equipment, the reverberation time of common areas, partition areas, room volumes, and the acoustic characteristics of partitions and other surfaces are also important.

The effect of pollution on the human body depends on the type and amount of pollutants, the concentrations of other pollutants, the individual sensitivity of a person, the duration of exposure to pollutants, etc. Control over the concentrations of pollutants also plays an important role. For this purpose, smart sensor networks are designed to continuously collect information processed by cost-effective optimisation and forecasting models.

Building management systems are becoming digital communication hubs closely linked to the growing importance of data analysis and the increasing collection of information from equipment, facilities and interconnected endpoints. Cameras and surveillance equipment generate huge amounts of data, and various environmental sensors, smartphones and other end-user devices form system components for continuous data collection. Artificial intelligence methods allow for analysing and interpreting data and making more efficient decisions on a real-time basis.

The paper aims to assess variations in air pollution and noise levels in the office space under different conditions, calculate the values of the correlation coefficients of parameters evaluating indoor air pollution, and determine the level of their stochastic interdependence.

2. Materials and Methods

To assess variations in air pollution and noise levels indoors during 4 weeks in a smart building situated at 5 T. Narbuto Street in Vilnius, the location of the smart building selected for research purposes is shown in Fig. 1. **The Business Center located in T. NARBUTO 5, Vilnius was chosen as a research object because it is one of the few modern smart houses with an automatically regulated ventilation system in Vilnius.** T. Narbuto Street is a high-intensity area with cars, trucks and public transport. According to the online application for traffic flow analysis provided by municipal enterprise *Susisiekimo paslaugos*, the average vehicle flow on T. Narbuto street in a single direction reaches approximately 15000-20000 vehicles per day during the analysed period.

The sensors recording air pollutant concentrations and noise levels were exhibited in a room on the 4th floor having windows facing south. The smart meter Ecomlite (France) measured indoor air parameters and transmitted the obtained data at fixed time intervals (every 1 minute) to the server via Wi-Fi connection (Fig. 2). This model can be integrated into building management systems such as a 'smart home' system. Technologies that should send out a signal of deterioration and ensure high air quality are intended for use by the consumer. The technical specifications of the smart indoor parameter meter are as follows:

- PM_{2.5} (particulate matter of up to 2.5 μm), measurement interval 0-1000 μg/m³, error > 100 μg/m³ ± 15%; < 100 μg/m³ ± 15 μg/m³;
- PM₁₀ (particulate matter of up to 10 μm), measurement interval 0-1000 μg/m³, error > 100 μg/m³ ± 15%; < 100 μg/m³ ± 15 μg/m³;

- CO₂ (carbon dioxide), measurement interval 400-2000 ppm, error 50 ppm of the full scale;
- Noise level, measurement interval 30-80 dB, error 1 dB;
- Operating environmental parameters: temperature -10...+45°C, relative humidity 10-85%;
- Temperature. Measurement interval -40°C...85°C, error 0.5°C;
- Relative humidity. Measurement interval 0-100%, error 3%;
- Atmospheric pressure. Measurement interval 300-1100 hPa, error 0.12 hPa.

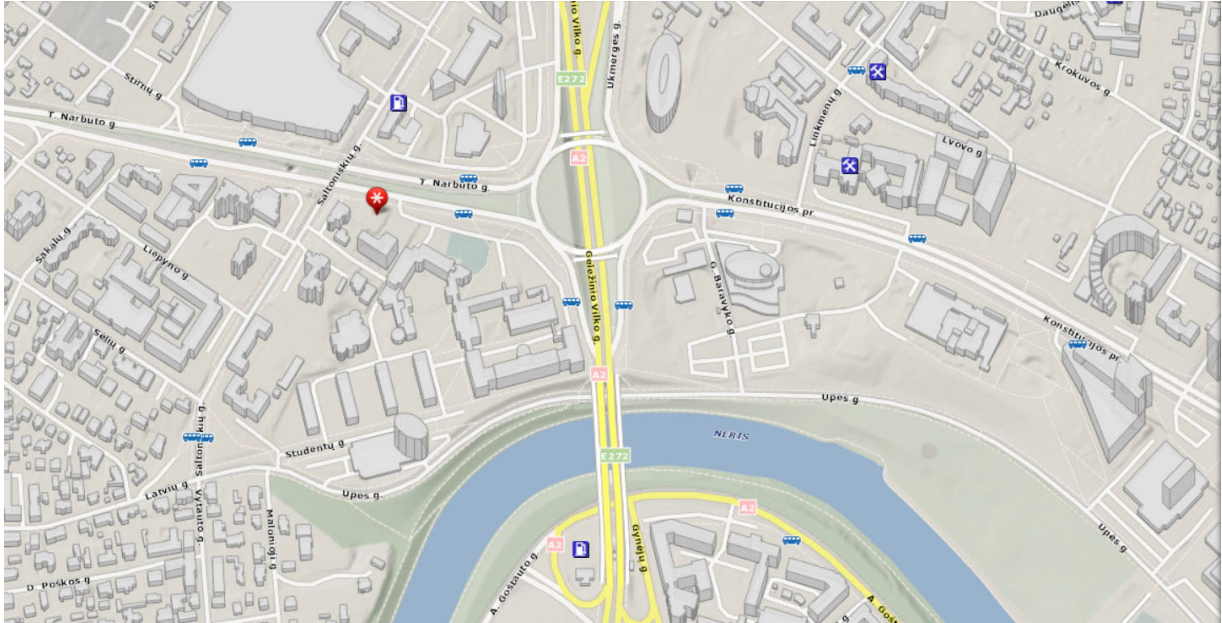


Fig. 1. The location of the building selected for research purposes at 5 T. Narbuto Street in Vilnius



Fig. 2. Smart indoor air quality measurement system ECOMLITE

The network of smart sensors is designed to continuously collect indoor air quality information processed by cost-effective optimisation and forecasting models. The data obtained from sensors are analysed and assessed using specific software. **Measurement data are not freely available, and we could use server data till 2022 year. We chose to measure the specified air pollutants (PM2.5, PM10 and CO₂) and noise since the main purpose of the research was to evaluate those parameters that change mainly due to the activities carried out inside the building.**

An integrated air purification unit was installed on the third floor of the examined smart building to reduce the concentrations of air pollutants indoors and to decrease a negative impact on employees' health. Such solutions are necessary on the premises where air quality plays a crucial role, such as manufacturing plants, educational and medical institutions, office space, etc.

The integrated air purification unit comprises an electrostatic precipitator with a pre-filter and a cartridge filter removing particulate matter (PM2.5 and PM10) from the indoor air. The location of the integrated air purification unit was preferred to be technical premises to reduce the noise experienced by the office staff and avoid additional air pollution under the operation of the integrated air purification unit. The air was taken from the room on the 3rd floor, purified, and entered the 4th floor, equipped with a smart interactive system for indoor room quality management and air pollution abatement. This floor employs premises for office work. Particulate matter, aerosols and gaseous pollutants are removed from the air, thus taking it back to the premises on the 3rd floor where the integrated air purification unit is located and the air treatment cycle is repeated.

Indoor air quality determines human comfort, productivity and health. Thus, the amount of the air supplied for the ventilation of low-energy buildings is set at not less than 1.2 m³/(h·m²) in Norway and Germany, 1.08 m³/(h·m²) in Denmark and 0.7 m³/(h·m²) in Lithuania (STR 2.01.02:2016).

The theory of covariance functions was used to analyse air pollution and noise detection sensor parameters. Variations in the correlation of pollution parameters of the time scale subject to fluctuations in time intervals, i.e. varying quantisation intervals, were established.

The analysis of variations in the normalised autocovariance and cross-covariance functions of the vectors φ of air pollution sensor parameters was conducted under a quantisation step change equal to 1 minute. The normalised values of the autocovariance function show variations in the correlation coefficients of the individual pollution parameters under fluctuations in the time interval, i.e. subject to quantisation intervals. The normalised values of the cross-correlation function point to the values of the cross-correlation coefficients of one or two pollution parameters (pairs of all parameters used) in the respective quantisation intervals. The figures show the quantisation interval on the abscissa axes while the values of the normalised covariance functions (values of correlation coefficients) are displayed on the ordinate axes.

The theoretical model of covariance functions is based on the concept of the stationary random function considering that the measurement errors of field parameters are random and possibly systemic, i.e. the mean error is equal to $M\Delta = \text{const} \rightarrow 0$ and dispersion makes $D\Delta = \text{const}$, when the covariance function of digital signals is subject only to difference in arguments, i.e. the quantisation interval on the time scale. The operator of Excel 2016 and Matlab 7 software packages was used to process data and create, select, and process the mathematical model.

The covariance functions of two digital vectors of air pollution and noise level parameters and the estimates of the covariance function of a single vector are calculated by transmitting digital data vectors in the form of random functions. Discrete transformation is used for processing digital signals (Antoine 2000, Dutkay & Jorgensen 2004, Koch 2000).

Each week, data vector φ for parameter measurement eliminates the data trend of measuring that vector. In line with data on the vectors φ of air pollution sensor parameters, the formed random functions will be considered stationary (broadly), i.e., the mean equals $M\{\varphi(t)\} \rightarrow \text{const}$, and the covariance function $K_\varphi(\tau)$ is only subject to the difference in arguments τ . The autocovariance function of a single random vector or the cross-covariance function of two random vectors have the form of $K_\varphi(\tau)$ (Koch 2000, Skeivalas et al. 2008):

$$K_\varphi(\tau) = M\{\delta\bar{\varphi}_1(u) \cdot \delta\bar{\varphi}_2(u + \tau)\}, \quad (1)$$

or

$$K_\varphi(\tau) = \frac{1}{T-\tau} \int_0^{T-\tau} \delta\varphi_1(u) \delta\varphi_2(u+\tau) du, \quad (2)$$

where:

$\delta\varphi_1 = \varphi_1 - \bar{\varphi}_1$ $\delta\varphi_2 = \varphi_2 - \bar{\varphi}_2$ – centred vectors φ under the eliminated trend,
 u – vector parameter,

$\tau = k \cdot \Delta$ – varying quantisation interval,
 k – the number of the units of measurement,
 Δ – the value of the unit of measurement,
 T – time,
 M – the symbol of the mean.

With reference to the available measurement data on air pollution sensor parameters, the estimate of the covariance function $K'_\varphi(\tau)$ is calculated in consonance with the below formula:

$$K'_\varphi(\tau) = K'_\varphi(k) = \frac{1}{n-k} \sum_{i=1}^{n-k} \delta\varphi_1(u_i) \delta\varphi_2(u_{i+k}), \quad (3)$$

where:

n – the general number of discrete intervals.

Formula (3) can be applied as the autocovariance or cross-covariance functions. In the case of the autocovariance function, vectors $\varphi_1(u)$ and $\varphi_2(u+\tau)$ are the parts of single vectors, whereas the cross-covariance function takes two different vectors.

The estimate of the normalised covariance function is expressed using the following formula:

$$R'_\varphi(k) = \frac{K'_\varphi(k)}{K'_\varphi(0)} = \frac{K'_\varphi(k)}{\sigma_\varphi^2}, \quad (4)$$

where:

σ'_φ – the estimate of the standard deviation of the random function.

The formula used for eliminating the data trend vector of digital measurement takes the form of:

$$\delta\varphi = \varphi - \bar{\varphi}, \quad (5)$$

where:

$\delta\varphi$ – data vector under the eliminated trend,

$\bar{\varphi}$ – vector trend.

The estimate of the covariance matrix of the i -th vector of air pollution sensor parameters takes the form of:

$$K'(\delta\varphi_i) = \frac{1}{n-1} \delta\varphi_i^T \delta\varphi_i. \quad (6)$$

The estimate of the cross-covariance matrix between the two vectors i and j of air pollution sensor parameters is expressed by the formula:

$$K'(\delta\varphi_i, \delta\varphi_j) = \frac{1}{n-1} \delta\varphi_i^T \delta\varphi_j, \quad (7)$$

where the dimensions of vectors $\delta\varphi_i, \delta\varphi_j$ must be equal.

The estimates of covariance functions $K'(\delta\varphi_i)$ and $K'(\delta\varphi_i, \delta\varphi_j)$ are reduced into the estimates of the matrices of correlation coefficients $R'(\delta\varphi_i)$ and $R'(\delta\varphi_i, \delta\varphi_j)$:

$$R'(\delta\varphi_i) = D_i^{-1/2} K'(\delta\varphi_i) D_i^{-1/2}, \quad (8)$$

$$R'(\delta\varphi_i, \delta\varphi_j) = D_{ij}^{-1/2} K'(\delta\varphi_i, \delta\varphi_j) D_{ij}^{-1/2}, \quad (9)$$

where D_i, D_{ij} are the diagonal matrices of the main diagonal members of the estimates of the corresponding covariance matrices $K'(\delta\varphi_i)$ and $K'(\delta\varphi_i, \delta\varphi_j)$.

The accuracy of the calculated correlation coefficients is defined by standard deviation σ_r , estimating the value of deviation according to the formula:

$$\sigma_r = \frac{1}{\sqrt{k}}(1 - r^2), \quad (10)$$

where $k = 1010$, r – correlation coefficient. The maximum estimate of standard deviation is obtained when the value of r is close to zero and in our case $\sigma_r' = 0.03$; when $r = 0.5$ it makes $\sigma_r' = 0.02$.

3. Results and Discussion

The concentrations and noise levels of air pollutants were continuously recorded every week from 00:01 a.m. Monday to 11:59 p.m. Sunday from 24 February to 22 March 2020.

Measurements lasted 4 weeks and covered 4 different stages:

Stage 1 covered the period from 24 February to 1 March 2020. The research room contained the switched-on mechanical ventilation system of the building and the switched-off integrated air purification unit.

Stage 2 covered the period from 2 to 8 March 2020. The research room contained the switched-off mechanical ventilation system and the integrated air purification unit.

Stage 3 covered the period from 3 to 15 March 2020. The research room contained the switched-on integrated air purification unit and the building's mechanical ventilation system.

Stage 4 covered the period from 16 to 22 March 2020. The research room contained the switched-on integrated air purification unit and the building's mechanical ventilation system. No office work was done due to the quarantine announced in Lithuania.

3.1. Research on the concentrations of PM_{2.5}, PM₁₀ and CO₂

Over four weeks, research on PM_{2.5} concentrations was assessed by continuous monitoring, and data on the conducted research findings are presented in Fig. 3.

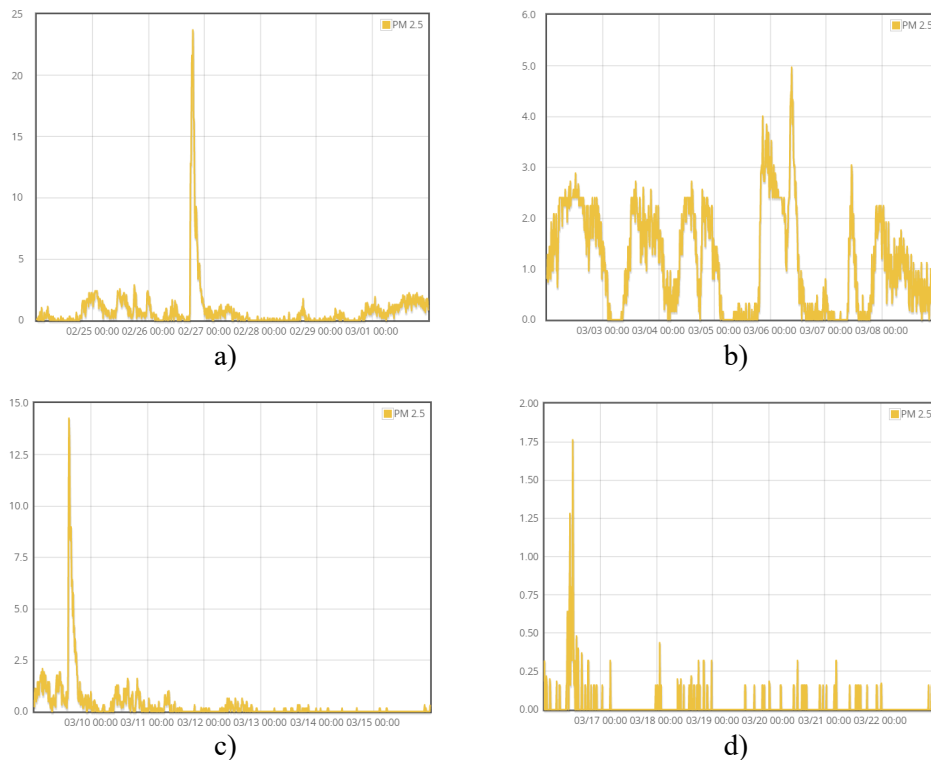


Fig. 3. Variations in PM_{2.5} concentration inside the office premises: a) 24 February – 1 March; b) 2-8 March; c) 9-15 March; d) 16-22 March

Stage 1. During the 1st week of the conducted research (24 February – 1 March 2020), PM_{2.5} concentration fluctuated from 0.0 to 12.82 $\mu\text{g}/\text{m}^3$ on working days. The highest PM_{2.5} concentration was recorded on Wednesday around 6 p.m. and reached 12.82 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Tuesday around 6 p.m. (2.89 $\mu\text{g}/\text{m}^3$) and Thursday around 10 a.m. (1.29 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM_{2.5} concentration ranged from 1.0 to 2.56 $\mu\text{g}/\text{m}^3$ with an average of 1.59 $\mu\text{g}/\text{m}^3$ (Fig. 3a).

Stage 2. During the 2nd week of the conducted research (2-8 March 2020), PM_{2.5} concentration fluctuated from 0.0 to 4.97 $\mu\text{g}/\text{m}^3$ on working days. The highest PM_{2.5} concentration was recorded on Friday around 9 a.m. and reached 4.97 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Monday around 12 noon (2.89 $\mu\text{g}/\text{m}^3$) and Tuesday around 2 p.m. (2.72 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM_{2.5} concentration ranged from 1.0 to 3.05 $\mu\text{g}/\text{m}^3$ with an average of 1.52 $\mu\text{g}/\text{m}^3$ (Fig. 3b).

Stage 3. During the 3rd week of the conducted research (3-15 March 2020), PM_{2.5} concentration fluctuated from 0.0 to 14.42 $\mu\text{g}/\text{m}^3$ on working days. The highest PM_{2.5} concentration was recorded on Monday around 2.40 p.m. and reached 14.42 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Tuesday around 3.30 p.m. (1.60 $\mu\text{g}/\text{m}^3$) and on Wednesday around 9 a.m. (1.0 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM_{2.5} concentration ranged from 0 to 0.32 $\mu\text{g}/\text{m}^3$ with an average of 0.08 $\mu\text{g}/\text{m}^3$. PM₁₀ concentration ranged from 2.4 to 5.49 $\mu\text{g}/\text{m}^3$ with an average of 3.20 $\mu\text{g}/\text{m}^3$ (Fig. 3c).

Stage 4. During the 4th week of the conducted research (16-22 March), PM_{2.5} concentration fluctuated from 0.0 to 1.76 $\mu\text{g}/\text{m}^3$ on working days. The highest PM_{2.5} concentration was recorded on Monday around 12 noon, reaching 1.76 $\mu\text{g}/\text{m}^3$. On other days, PM_{2.5} concentration was close to 0.0 $\mu\text{g}/\text{m}^3$. **At the weekend**, PM_{2.5} concentration ranged from 0 to 0.48 $\mu\text{g}/\text{m}^3$ with an average of 0.09 $\mu\text{g}/\text{m}^3$ (Fig. 3d).

The relationship between PM_{2.5} and PM₁₀ concentrations depends on the origin of particulate matter. During our measurements, PM_{2.5} concentration ranged from 30 to 80% of PM₁₀.

For four weeks, research on PM₁₀ concentrations was assessed through continuous monitoring, and the findings are presented in Fig. 4.

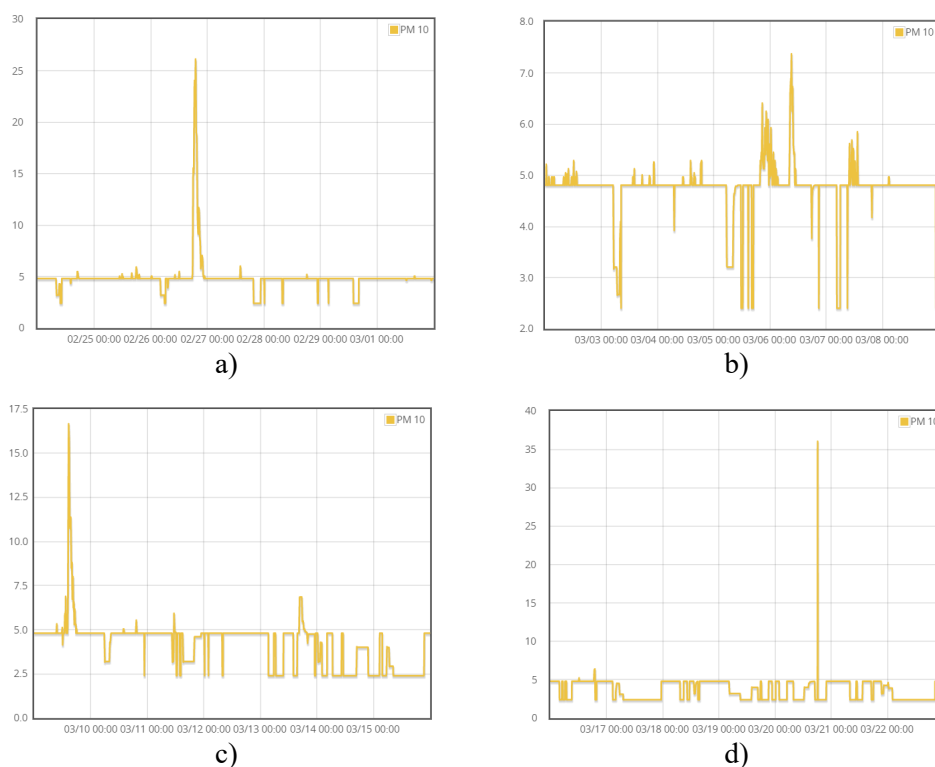


Fig. 4. Variations in PM₁₀ concentration inside the office premises: a) 24 February – 1 March; b) 2-8 March; c) 9-15 March; d) 16-22 March

Stage 1. During the 1st week of the conducted research (24 February – 1 March 2020), PM₁₀ concentration fluctuated from 2.40 to 15.22 $\mu\text{g}/\text{m}^3$ on working days. The highest PM₁₀ concentration was recorded on Wednesday around 6 p.m. and reached 15.22 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Tuesday around 6 p.m. (5.93 $\mu\text{g}/\text{m}^3$) and Thursday around 2 p.m. (6.10 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM₁₀ concentration ranged from 2.4 to 5.21 $\mu\text{g}/\text{m}^3$ with an average of 4.70 $\mu\text{g}/\text{m}^3$ (Fig. 4a).

Stage 2. During the 2nd week of the conducted research (2-8 March 2020), PM10 concentration fluctuated from 2.40 to 7.37 $\mu\text{g}/\text{m}^3$ on working days. The highest PM10 concentration was recorded on Friday around 9 a.m. and reached 7.37 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Monday around 12 noon (5.29 $\mu\text{g}/\text{m}^3$) and Wednesday around 2 p.m. (5.29 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM10 concentration ranged from 2.4 to 5.85 $\mu\text{g}/\text{m}^3$ with an average of 4.75 $\mu\text{g}/\text{m}^3$ (Fig. 4b).

Stage 3. During the 3rd week of the conducted research (3-15 March 2020), PM10 concentration fluctuated from 2.40 to 16.91 $\mu\text{g}/\text{m}^3$ on working days. The highest PM10 concentration was recorded on Monday around 2.40 p.m. and reached 16.91 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Wednesday around 11.20 a.m. (5.94 $\mu\text{g}/\text{m}^3$) and on Friday around 4.45 p.m. (6.87 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM10 concentration ranged from 2.4 to 5.49 $\mu\text{g}/\text{m}^3$, averaging 3.20 $\mu\text{g}/\text{m}^3$ (Fig. 4c).

Stage 4. During the 4th week of the conducted research (16-22 March), PM10 concentration fluctuated from 2.40 to 5.25 $\mu\text{g}/\text{m}^3$ on working days. The highest PM10 concentration was recorded on Monday around 12.20 p.m. and reached 5.25 $\mu\text{g}/\text{m}^3$. Lower concentrations were recorded on Wednesday between 9 and 10 a.m. (4.81 $\mu\text{g}/\text{m}^3$), on Thursday around 6 p.m. (4.81 $\mu\text{g}/\text{m}^3$) and Friday around 4.30 p.m. (4.81 $\mu\text{g}/\text{m}^3$). **At the weekend**, PM10 concentration ranged from 2.4 to 36.06 $\mu\text{g}/\text{m}^3$ with an average of 3.50 $\mu\text{g}/\text{m}^3$ (Fig. 4d).

For the four weeks, research on CO₂ concentrations was assessed through continuous monitoring, and the findings are presented in Fig. 5.

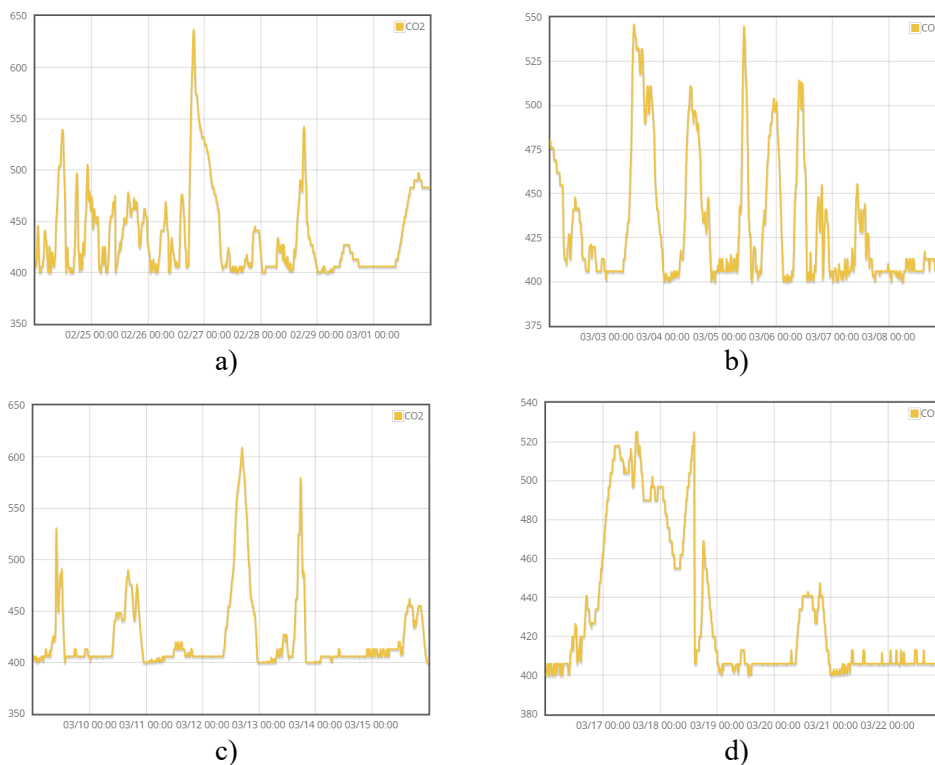


Fig. 5. Variations in CO₂ concentration inside the office premises: a) 24 February – 1 March; b) 2-8 March; c) 9-15 March; d) 16-22 March

Recalculating CO₂ concentration from ppm to mg/m³ is possible, but it depends on atmospheric temperature and pressure. Due to this, recalculation is problematic, and we presented the CO₂ data in ppm. The concentration level of CO₂ was 400 to 609 ppm, corresponding to approximately 700-1150 mg/m³.

Stage 1. During the 1st week of the conducted research (24 February – 1 March 2020), CO₂ concentration fluctuated from 400.0 to 539 ppm on working days. The highest CO₂ concentration was recorded on Monday around 11.30 a.m. and reached 539 ppm. Lower concentrations were recorded on Wednesday around 6 p.m. (520.8 ppm) and Friday around 6 p.m. (515.7 ppm). **At the weekend**, CO₂ concentration ranged from 400 to 542.27 ppm, averaging 431.46 ppm (Fig. 5a).

Stage 2. During the 2nd week of the conducted research (2-8 March 2020), CO₂ concentration fluctuated from 400.0 to 546 ppm on working days. The highest CO₂ concentration was recorded on Tuesday around 11.30 a.m. and reached 546 ppm. Lower concentrations were recorded on Wednesday around 11.30 a.m. (511 ppm) and Thursday around 10.20 a.m. (546 ppm). **At the weekend**, CO₂ concentration ranged from 400 to 455.47 ppm, averaging 411.36 ppm (Fig. 5b).

Stage 3. During the 3rd week of the conducted research (3-15 March 2020), CO₂ concentration fluctuated from 400.0 to 609 ppm on working days. The highest CO₂ concentration was recorded on Thursday around 4.40 p.m. and reached 609 ppm. Lower concentrations were recorded on Monday around 9.40 a.m. (531.07 ppm) and on Friday around 6 p.m. (579.6 ppm). **At the weekend**, CO₂ concentration ranged from 400 to 535.27 ppm with an average of 415.79 ppm (Fig. 5c).

Stage 4. During the 4th week of the conducted research (16-22 March), CO₂ concentration fluctuated from 400.0 to 525 ppm on working days. The highest CO₂ concentration was recorded on Tuesday around 2 p.m. and Wednesday around 2 p.m., reaching 525 ppm. Lower concentrations were recorded on Friday around 2 p.m. (442.87 ppm). **At the weekend**, CO₂ concentration ranged from 400 to 447.53 ppm, averaging 408.43 ppm (Fig. 5d).

Research on the noise level. For the four weeks, variations in the equivalent noise level were assessed through continuous monitoring, and the findings are presented in Fig. 6.

At stage 1 (Fig. 6a), the values of the noise level ranged from 36.2 to 59.0 dB. The maximum noise levels set during working hours at the daytime fluctuated between 57 and 59 dB. The noise level established in the premises during working hours was mainly influenced by the staff working in the office. The analysis of the noise levels determined in the hours after the work shift (i.e. from 6 p.m.) shows that noise levels remained constant, almost unchanged and peaked at 37 dB. The same tendency was observed at the weekend when the noise level values were constant and did not exceed 37 dB.

At stage 2, the research room contained the switched-off ventilation and conditioning systems of the building, and the noise level values were found to vary from 37.6 to 49.0 dB. At weekends, the values of the background noise level were around 38 dB. Also, the observed isolated, short-lived noise signals may have been caused by the sources of the urban environment. The maximum noise levels set during the day were about 15% lower than the maximum values established at stage 1 (Fig. 6b).

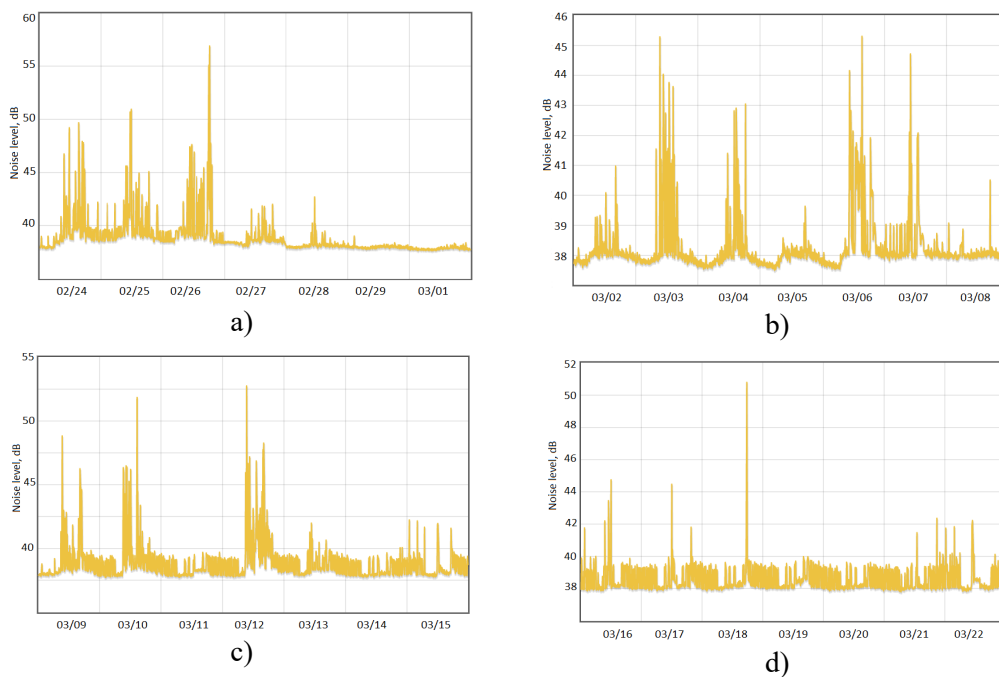


Fig. 6. Variations in the noise level inside the office premises: a) 24 February – 1 March; b) 2-8 March; c) 9-15 March; d) 16-22 March

At stage 3, the research room contained the integrated air purification unit connected to the air supply and exhaust system. Noise level studies performed at stage 3 show that the maximum noise levels reached 54 dB (Fig. 6c). The background noise level was around 38 dB. These values were recorded over the weekend and within the periods that coincided with the time after the work shift, which may have been influenced by the noise level of the building engineering systems and service equipment, such as ventilation and refrigeration systems.

At stage 4, from 16 to 22 March, no office work was done due to the announced quarantine. Thus, during this period, short-term isolated noise signals that may have been caused by the engineering systems of the building or the changing characteristics of the urban environment were observed (Fig. 6d). This creates uncertainties regarding the collection of actual measurement results and the duration of exposure of the subjects having the greatest effects on findings.

The summarised results of the research on the noise level demonstrate that the average noise levels established in the investigated premises of the office building do not exceed the recommended limit value of 40 dB applied in design requirements for the newly built office buildings. The maximum noise levels in the office premises ranged from 55 to 59 dB and were determined during working hours in the daytime only. However, the greatest uncertainties arise in the case of assessing the factors most affecting the obtained results, which depend, in particular, on the nature and duration of activity performed by the staff working on the investigated premises.

3.2. Parameter Analysis Applying the Method of Covariance Functions

The obtained measurement results formed data arrays of 4 vectors each week. Data were recorded at time intervals $\tau_{\Delta} = 1$ min for 4 weeks. Each vector contained $n = 2020$ measurement values. The vectors estimating standard deviation (Table 1) describe the accuracy of parameter vectors. The vectors mentioned above are numbered sequentially into 1, 2, 3, 4...

Vector measurement data were processed in line with the created computer programs applying Matlab 7 software package operators.

The values of the quantisation interval of the normalised covariance functions range from 1 to $n/2$ values, where $n = 2020$ is the number of the values of each vector. The estimate $K'_{\varphi}(\tau)$ of the normalised autocovariance function $K_{\varphi}(\tau)$ for each vector was calculated, and the graphical expressions of 4 normalised autocovariance functions were obtained each week. Also, the estimates of the normalised cross-covariance functions $K'_{\varphi}(\tau)$ for all 4 vectors were calculated in consonance with all 4 vectors and 6 graphical expressions were obtained.

The normalised autocovariance functions of the vectors having similar parameters have different graphical expressions over all weeks. The noise-normalised autocovariance functions acquire the maximum value of the correlation coefficient $r \rightarrow 1.0$ at the values of the quantisation interval $k \rightarrow 0$ ($\tau_k \rightarrow 0$ min.) and further decrease to $r \rightarrow -0.3$ at the respective values of the quantisation interval. The values of autocovariance functions vary in the range of $r \rightarrow (1: -0.3)$ in all quantisation intervals over the 4 weeks. The first value shows the normalised standard deviation when $k \rightarrow 0$, and the second value points out variations in the corresponding noise under changes in the quantisation interval (Fig. 1-5). Thus, the density of noise pollutants is $r \rightarrow -0.3$, which is considered low.

The values of the autocovariance functions of pollutants PM2.5 and PM10 vary in the range of $r \rightarrow (1: -0.5)$ in all quantisation intervals during the 4 weeks. The density of particulate matter is moderate, as shown by the correlation in Fig. 1-8.

Table 1. Average requirements for the standard deviations of parameter vectors of noise and particulate matter

Weeks	Noise avg1, dB	Noise avg2, dB	PM2.5, $\mu\text{g}/\text{m}^3$	PM10, $\mu\text{g}/\text{m}^3$
1	1.0	0.1	2.0	1.8
2	0.5	1.1	1.0	0.5
3	1.6	1.3	1.0	1.3
4	0.7	0.8	0.1	1.1

The values of the normalised cross-covariance functions of noise parameter and chemical compound vectors range in the interval $r \rightarrow (0.5: -0.4)$ during the measurements of all weeks. Thus, the average cross-covariance between noise and chemical compound parameter vectors is noticed. The different graphical expressions of dependence variations are shown in Fig. 7.

The value of quantisation interval k increases when autocovariance $k \geq 600$ becomes negative, which indicates that a rise in the noise interval (quantisation interval) decreases correlation. Thus, the value of the correlation coefficient is proportional to the level of pollution (Fig. 7a). Meanwhile, Fig. 7b shows that an increase in the value of quantisation interval k , when $k \geq 100$, results in autocovariance close to zero. The correlation coefficient r value ranges in the zero range and denotes that the noise level fluctuated in the zero range under the varying quantisation interval.

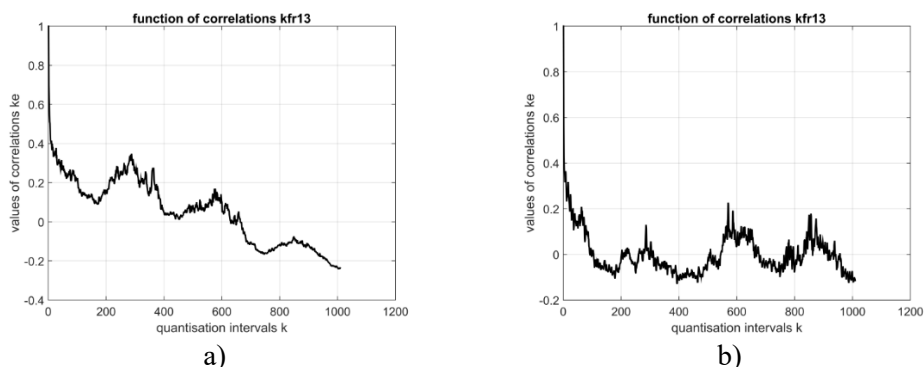


Fig. 7. The normalised autocovariance function of noise level vectors: a) noise avg1 (week 1); b) parameters of noise avg2 (week 3)

The values of the normalised cross-covariance functions of the vectors of particulate matter parameters and chemical compounds range in the interval $r \rightarrow (0.6: -0.5)$ during the measurements of all weeks. Therefore, the average cross-covariance between the vectors of physical parameters and chemical compounds is observed. The different graphical expressions of dependence variations are shown in Fig. 8.

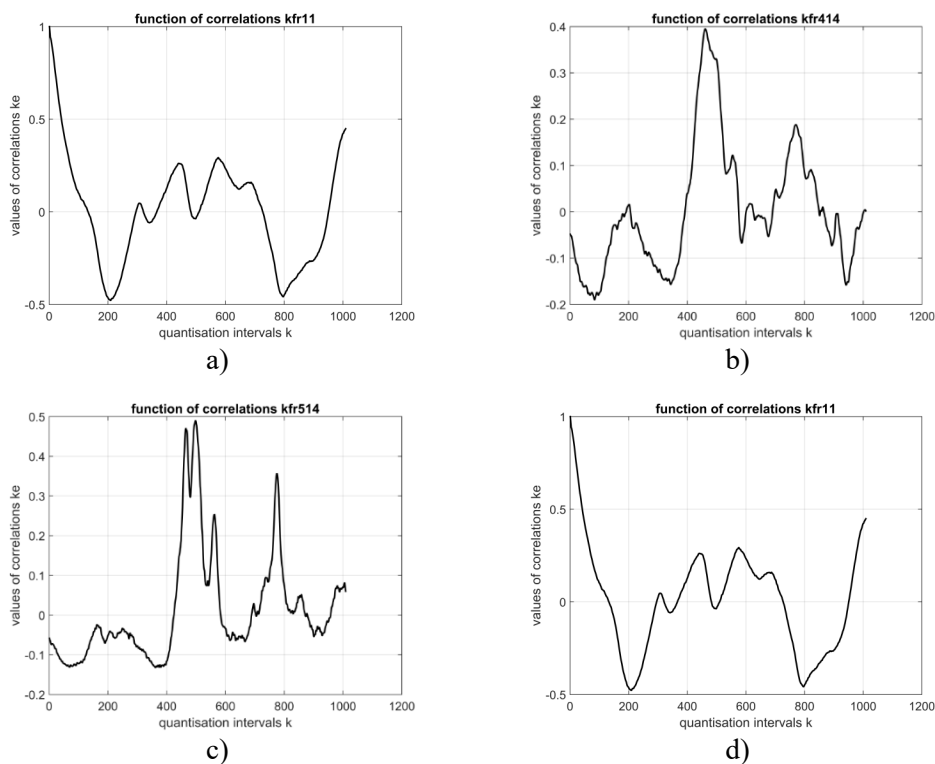


Fig. 8. The normalised autocovariance function of the parameter vector: a) parameters of PM 2.5 (week 1); b) noise avg1 parameters (week 2) and the normalised cross-covariance function of CO₂; c) noise avg2 parameters (week 3) and the normalised cross-covariance function of PM2.5; (d) the normalised autocovariance function of parameter vectors of particulate matter PM2.5 (week 1)

The values of pollution parameters of PM2.5 (Fig. 8 a) range in the interval $(1: -0.5)$. The rising quantisation interval results in varying correlation and thus pollution density in the negative range, which provides that an increase in quantisation interval k reduces particulate matter (Fig. 8 b). The figure shows a correlation in the $(0.4: -0.2)$ range. For this reason, the density of noise pollution, under an increase in quantisation range and an effect on CO₂, is variable in the average pollution range.

Fig. 8c shows a correlation in the $(0.5: -0.1)$ range. Consequently, growth in the noise quantisation interval increases the correlation between these vectors, which suggests that noise potentially adds to the density of particulate matter.

Fig. 8d shows the normalised autocovariance function of the parameter vector of particulate matter PM_{2.5} (week 1) where the values of autocovariance r vary in the range of $r \approx 1$: -0.5 under the increasing quantisation interval k , which points out that the density of particulate matter PM_{2.5} varied over a wide range under varying quantisation interval k .

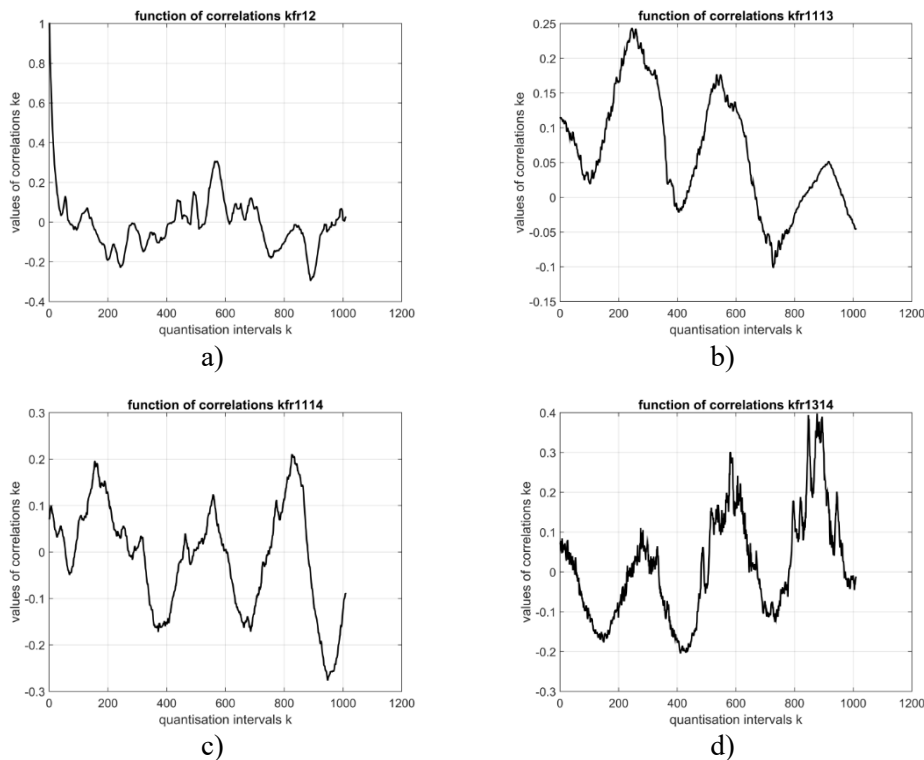


Fig. 9. The normalised cross-covariance function of the examined parameter vectors: a) parameters of particulate matter PM₁₀ (week 2); b) noise avg1 parameters (week 1) and PM_{2.5} vector; c) noise avg2 parameters (week 1) and PM₁₀ vector; d) vector of noise avg1 and avg2 parameters (week 1)

An increase in quantisation interval k exhibits variations in the values of autocovariance r in the range of $r \approx 1$: -0.3 . Fluctuations in quantisation interval k disclosed that the density of particulate matter PM₁₀ varied in the zone of the zero value (Fig. 9a). Fig. 9b shows a correlation in the range of $(0.25$: $-0.1)$. Thus, the increasing noise quantisation interval reduces the correlation between these vectors, which suggests that noise potentially lowers the density of particulate matter in an oscillating form.

Fig. 9c shows a correlation in the $(0.2$: $-0.3)$ range. As a result, increasing the noise quantisation interval leads to changes in the correlation between these vectors with decreasing oscillation in the zero value range. Noise may potentially affect the density of particulate matter in a fluctuating form.

Fig. 9d shows a correlation varying in the $(0.4$: $-0.2)$ range. Hence, a rise in the noise quantisation interval causes changes in the correlation between these vectors with increasing oscillation. Noise may potentially affect the density of particulate matter.

4. Conclusions

The data analysed during the 4-week research demonstrates that most peaks of air pollutant concentrations (maximum values) are recorded in the evening before the end of the working day, from 4 p.m. to 6 p.m. The highest concentrations of air pollutants studied during other working hours are less common. Therefore, it can be assumed that the above introduced situation is caused by the accumulation of pollutants in the room and/or the western peak of road traffic.

At stage 1, the average pollutant concentrations in the ventilated room ranged from 433.18 to 455.36 ppm of CO₂, from 1.78 to 1.90 $\mu\text{g}/\text{m}^3$ of PM_{2.5} and from 4.77 to 4.80 $\mu\text{g}/\text{m}^3$ of PM₁₀. The measured average concentrations of pollutants were significantly lower than the permissible values: CO₂ was made approximately 11 times, PM_{2.5} exceeded 13 times, and PM₁₀ exceeded 10 times.

At stage 2, the room was not ventilated. Thus, the average concentrations of all tested air pollutants increased compared to stage 1, when ventilation was active, except for the case of PM₁₀, the concentration of which remained similar. The average concentrations of pollutants reached 457.34 ppm of CO₂, 2.20 $\mu\text{g}/\text{m}^3$

of PM_{2.5} and 4.79 $\mu\text{g}/\text{m}^3$ of PM₁₀. The measured average concentrations of pollutants were significantly lower than the permissible values: CO₂ was made approximately 11 times, PM_{2.5} exceeded 11 times, and PM₁₀ exceeded 10 times.

At stage 3, ventilation was not switched on in the room, but the integrated air purification unit was operating and removing PM_{2.5} and PM₁₀ from the air. The average concentrations of all tested air pollutants decreased during stage 3 compared to stage 2 when ventilation did not work. The average concentrations of pollutants made from 435.17 to 447.27 ppm of CO₂, from 1.29 to 1.50 $\mu\text{g}/\text{m}^3$ of PM_{2.5} and from 3.47 to 4.05 $\mu\text{g}/\text{m}^3$ of PM₁₀. The measured average concentrations of pollutants were significantly lower than the permissible values: CO₂ exceeded 11 times, PM_{2.5} exceeded 16 times, and PM₁₀ made approximately 12 times.

The analysed data on 4 week research disclosed that the average and maximum concentration of none of the tested air pollutants in the room exceed the permissible concentration limits given in the Lithuanian Hygiene Norm HN 23:2011 or the concentration values set for ambient air. The average concentrations of the tested air pollutants were even lower than the occupational comfort conditions corresponding to the concentration values set by the World Health Organization: the maximum concentrations of PM₁₀ and CO₂ slightly exceeded the established comfort conditions.

The summarised results of the four-week noise level studies show that the average variation in noise levels is around 40 dB and, within error limits, coincides with the recommended limit value of 40 dB used in design requirements for the newly built office buildings. No increase in the noise level in the office premises after installing the integrated air purifier was detected.

The maximum noise levels (peaks) in the office premises ranged from 55 to 59 dB, were short-lived and determined only during working hours, thus leading to uncertainties in assessing the factors most influencing the findings, particularly subject to the nature and duration of activity performed by the staff working in the investigated premises.

The normalised autocovariance functions of the noise and particulate pollution parameter vectors have different graphical expressions each week. The values of autocovariance functions in all quantisation intervals over the 4 weeks vary in the range of $r \rightarrow (1: -0.3)$. The highest values of correlation coefficients have been found in the vectors of particulate matter parameters. The first value indicates the normalised standard deviation when $k \rightarrow 0$, and the second points to variations in the corresponding noise or particulate pollution under the ranging quantisation interval.

Noise density is low in the laboratory and varies for all 4 weeks in a small range of $r \rightarrow (1: -0.2)$. The values of the normalised cross-covariance functions of the vectors of noise parameters and chemical compounds varied in the range of $r \rightarrow (0.5: -0.4)$ during the measurements of all weeks. Thus, the average cross-covariance between noise and chemical compound parameter vectors exists.

The values of the normalised cross-covariance functions of particle parameter and chemical compound vectors vary in the range of $r \rightarrow (0.6: -0.5)$ during the measurements of all weeks. Consequently, the average cross-covariance exists between the vectors of physical parameters and the vectors of chemical compounds.

The normalised cross-covariance function of the vector of noise avg2 parameters (week 3) and PM_{2.5} vector has values in the range of $r \rightarrow (0.5: -0.1)$. Hence, the rising noise quantisation interval increases inter-correlation and possibly particle density.

References

- Antoine, J.P. (2000). Wavelet analysis of signals and images. *Revista Ciencias Matematicas*, 18, 113-143.
- Brace, M.D., Stevens, E., Taylor, S.M., Butt, S., Sun, Z., Hu, L., Borden, M., Khanna, N., Kuchta, J., Trites, J., Hart, R., Gibson, M.D. (2014). 'The air that we breathe': Assessment of laser and electrosurgical dissection devices on operating theater air quality. *Journal of Otolaryngology – Head & Neck Surgery*, 43(1), 39. <https://doi.org/10.1186/s40463-014-0039-1>
- Brdarić, D., Kovač-Andrić, E., Šapina, M., Kramarić, K., Lutz, N., Perković, T., Egorov, A. (2019). Indoor air pollution with benzene, formaldehyde, and nitrogen dioxide in schools in Osijek, Croatia. *Air Quality, Atmosphere & Health*, 12(8), 963-968. <https://doi.org/10.1007/s11869-019-00715-7>
- Canha, N., Mandin, C., Ramalho, O., Wyart, G., Ribéron, J., Dassonville, C., Hänninen, O., Almeida, S. M., Derbez, M. (2016). Assessment of ventilation and indoor air pollutants in nursery and elementary schools in France. *Indoor Air*, 26(3), 350-365. <https://doi.org/10.1111/ina.12222>
- Dumała, S.M., Dudzińska, M.R. (2013). Microbiological indoor air quality in Polish schools. *Rocznik Ochrona Środowiska*, 1, 231-244.
- Dutkay, D.E, Jorgensen P.E.T. (2004). Wavelets on fractals. *Revista Matemática Iberoamericana*, 22, 131-180.
- Gritzki, R., Rösler, M. (2013). Komfort für Passivhaus-Büros—Planungsunterstützung mit Hilfe gekoppelter Gebäude-, Anlagen-und Strömungssimulation. *Bauphysik*, 35(1), 8-15. <https://doi.org/10.1002/bapi.201310040>

- Heberle, S.M., Lorini, C., Rosa, M.S., Barros, N. (2019). Evaluation of bus driver exposure to nitrogen dioxide levels during working hours. *Atmospheric Environment*, 216(116906), 1-9. <https://doi.org/10.1016/j.atmosenv.2019.116906>
- Higashikubo, I, Miyauchi, H., Yoshida, S., Tanaka, S., Matsuoka, M., Arito, H., Araki, A., Shimizu, H., Sakurai, H. (2017). Assessment of workplace air concentrations of formaldehyde during and before working hours in medical facilities. *Industrial health*, 55(2), 192-198. <https://doi.org/10.2486/indhealth.2016-0147>
- Jung, C.C., Wu, P.C., Tseng, C.H., Su, H.J. (2015). Indoor air quality varies with ventilation types and working areas in hospitals. *Building and Environment*, 85, 190-195. <https://doi.org/10.1016/j.buildenv.2014.11.026>
- Koch, K.R. (2000). Einführung in die Byes-Statistik. Springer-Verlag Berlin Heidelberg, 224 p.
- Kogianni, E., Kouras, A., Samara, C. (2020). Indoor concentrations of PM 2.5 and associated water-soluble and labile heavy metal fractions in workplaces: implications for inhalation health risk assessment. *Environmental Science and Pollution Research*, 1-11. <https://doi.org/10.1007/s11356-019-07584-8>
- Kolarik, J., Toftum, J., Kabrhel, M., Jordan, F., Geiss, O., Kabele, K. (2015). Field measurements of perceived air quality and concentration of volatile organic compounds in four offices of the university building. *Indoor and Built Environment*, 24(8), 1048-1058. <https://doi.org/10.1177/1420326X14537283>
- Liu, J., Liang, Q., Oldham, M.J., Rostami, A.A., Wagner, K.A., Gillman, I., Patel, P., Savioz, R., Sarkar, M. (2017). Determination of selected chemical levels in room air and on surfaces after the use of cartridge-and tank-based e-vapor products or conventional cigarettes. *International journal of environmental research and public health*, 14(9):969, 1-21. <https://doi.org/10.3390/ijerph14090969>
- Madureira, J., Paciência, I., Rufo, J., Ramos, E., Barros, H., Teixeira, J.P., de Oliveira Fernandes, E. (2015). Indoor air quality in schools and its relationship with children's respiratory symptoms. *Atmospheric Environment*, 118, 145-156. <https://doi.org/10.1016/j.atmosenv.2015.07.028>
- Maliszewska, A., Szkarowski, A., Chernykh, A. (2019). Normative problems of the nitrogen oxides concentration limiting in the human residence environment. *Rocznik Ochrona Środowiska*, 2, 1328-1342.
- Pitarma, R., Marques, G., Ferreira, B.R. (2017). Monitoring indoor air quality for enhanced occupational health. *Journal of medical systems*, 41(2), 23, 1-8. <https://doi.org/10.1007/s10916-016-0667-2>
- Rivas, I., Viana, M., Moreno, T., Pandolfi, M., Amato, F., Reche, C., Bouso, L., Álvarez-Pedrerol M., Alastuey, A., Sunyer, J., Querol, X. (2014). Child exposure to indoor and outdoor air pollutants in schools in Barcelona, Spain. *Environment international*, 69, 200-212. <https://doi.org/10.1016/j.envint.2014.04.009>
- Salama, K.F., Berekaa, M.M. (2016). Assessment of air quality in Dammam slaughter houses, Saudi Arabia. *International Journal of Medical science and public Health*, 5(2), 287-291. <https://doi.org/10.5455/ijmsph.2016.10092015121>
- Serafimova, E., Petkova, V., Kostova, B. (2015). In: 11th Scientific Conference with International Participation SPACE, ECOLOGY, SAFETY (pp. 4-6).
- Skeivalas, J. (2008). *GPS tinklų teorija ir praktika* [Theory and practice of GPS networks]. Vilnius: Technika. 288 p.
- Staszowska, A. (2020). Application of Biophilic Installations for Indoor Air Quality Improvement. *Rocznik Ochrona Środowiska*, 2, 716-726.
- STR 2.01.02:2016. Pastatų energinio naudingumo projektavimas ir sertifikavimas. (Design and certification of energy performance of buildings). Vilnius, 2016.
- Traumann, A., Tint, P. (2014). *Qualitative and quantitative determination of chemicals and dust in the air of the work environment*. In: Environmental Engineering. Proceedings of the International Conference on Environmental Engineering. ICEE (Vol. 9). Vilnius Gediminas Technical University, Department of Construction Economics & Property. 1-10.
- Zorpas, A.A., Skouroupatis, A. (2015). Indoor air quality evaluation of two museums in a subtropical climate conditions. *Sustainable Cities and Society*, 20, 52-60. <https://doi.org/10.1016/j.scs.2015.10.002>