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# INSTRUMENTAL MONITORING OF AIR POLLUTION FROM POWER GENERATORS WITH AI-BASED DATA ANALYSIS: METHODOLOGY AND RISK ASSESSMENT

**Purpose.** To instrumentally assess the impact of electric generators on ambient air quality and acoustic load in the central part of the city of Dnipro, as well as to test elements of artificial intelligence for the analysis of the spatial distribution of pollutants.

**Methodology.** A series of field measurements of carbon monoxide (CO), nitrogen oxides ($NO_x$), particulate matter (PM), and noise levels were conducted at fixed monitoring points along Dmytro Yavornytskyi Avenue under background conditions and during generator operation. Data processing included statistical analysis, normalization of indicators, and clustering using machine learning techniques to identify spatial patterns and variations in pollutant concentrations and acoustic levels.

**Findings.** The study identified the formation of localized zones of elevated air pollution and increased acoustic load in the immediate vicinity of operating generators. During generator operation, increased concentrations of CO, $NO_x$, and PM, as well as higher noise levels, were recorded compared to background conditions. AI-based analysis enabled the differentiation of zones with varying degrees of environmental risk within the investigated urban area.

**Originality.** For the first time, an integrated methodology has been developed and tested for assessing cumulative environmental risk in conditions of extremely high density of autonomous power sources (up to 24 units per 1 km of building frontage) within the specific topography of a 'street canyon'. The originality lies in the identified patterns of formation of local pollution 'hotspots', where $PM_{2.5}$ concentrations exceed EEA international standards by 12–15 times. A new approach is proposed to verifying anthropogenic pollution loads using a *k*-means clustering algorithm, which allows the contribution of individual sources to be distinguished from the city-wide background with a level of accuracy unattainable by fixed monitoring stations.

**Practical value.** The results obtained can be used to develop recommendations for the placement of electric generators in urban environments and to improve local environmental monitoring systems in emergency power supply conditions. Based on the established dispersion patterns (1.5–2 times decrease in concentrations at a distance of 4–6 meters), it is recommended to establish a minimum distance of generators from pedestrian breathing lines and building entrances of at least 5 meters, as well as the mandatory use of vertical exhaust pipes with a height of more than 2.5 meters for the release of gases beyond the surface layer.

**Keywords:** *generator, air quality, noise, urban areas, artificial intelligence, environmental safety*

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**Introduction.** Conditions of energy instability caused by military conflicts, natural disasters, or infrastructure deterioration lead to the widespread use of autonomous power sources in urban areas. In many countries worldwide, backup gasoline and diesel generators become a temporary alternative to centralized energy systems, forming new types of localized anthropogenic pressure on the environment.

Following the onset of large-scale power outages in Ukraine, the use of gasoline and diesel generators has become widespread. Under conditions of destruction of energy infrastructure facilities and prolonged blackouts, these devices have become critically important for maintaining the functioning of residential, commercial, and governmental facilities. At the same time, the rapid increase in the number of operating generators in the urban environment is accompanied by significant environmental risks that have not yet been adequately studied at the level of specific streets or neighborhoods.

Generators are localized sources of atmospheric pollution, as the combustion of diesel or gasoline fuel results in the emission of carbon monoxide (CO), nitrogen oxides ($NO_x$), particulate matter (PM), sulfur compounds, and other products of incomplete combustion. Unlike motor vehicles, these units are generally not equipped with exhaust filtration or treatment systems and therefore intensively pollute the air even during short periods of operation. In addition to chemical impacts, generators produce significant noise pollution, with sound pressure levels near the device reaching 80–100 dBA, which substantially exceeds the maximum permissible levels for residential areas [1].

Unlike stationary industrial sources or traffic flows, the impact of generators is localized and point-based, occurring directly within the population's breathing zone. This type of pollution is characterized by high

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spatial variability, which complicates its detection by conventional stationary monitoring stations oriented toward assessing the overall urban background.

The problem is further complicated by the fact that the use of generators in Ukrainian cities is currently virtually unregulated. Under martial law conditions, certain restrictions, including sanitary noise standards and permits for pollutant emissions, are temporarily not enforced [2]. Generators formally do not fall under the definition of stationary emission sources and therefore remain outside the scope of standard environmental supervision [3]. In most cities, they are installed directly on sidewalks or beneath building windows, creating a high risk of localized pollution [4].

Thus, despite the evident scale of generator use in urban environments, comprehensive instrumental studies combining local monitoring of emissions and noise with spatial data analysis using artificial intelligence methods are lacking. This limits the possibilities for quantitative assessment of environmental risk and the development of scientifically grounded recommendations for regulating their placement.

**Literature review.** Medical studies indicate a direct relationship between exposure to fine particulate matter ($PM_{2.5}$), nitrogen oxides, and carbon monoxide and impairments of the respiratory, cardiovascular, and nervous systems [5, 6]. According to the global guidelines of the World Health Organization, even relatively low concentrations of $PM_{2.5}$ and $NO_2$ are associated with an increased risk of chronic diseases and premature mortality [6]. Diesel exhaust has been classified by the International Agency for Research on Cancer as carcinogenic to humans (Group 1) [7], underscoring the hazards of using diesel generators in densely built urban environments.

Carbon monoxide (CO) is particularly dangerous, as it blocks oxygen transport in the body and can lead to fatal poisoning when accumulated in enclosed or semi-enclosed spaces. Studies of poisoning cases resulting from the use of portable generators demonstrate a significant number of hospitalizations and fatalities during periods of energy crises [8, 9]. Thus, generators pose not only an environmental but also a direct toxicological risk to the population.

In addition to chemical impacts, acoustic exposure is a significant factor. Prolonged noise exposure is associated with elevated levels of stress hormones, arterial hypertension, sleep disturbances, and decreased cognitive function [10, 11]. Studies of noise from diesel generators in countries with unstable energy systems confirm exceedances of permissible levels and chronic acoustic discomfort in areas where small businesses are located [12].

International studies show that under conditions of widespread use of backup diesel generators, they can account for a substantial share of urban NOx and PM emissions, particularly in the absence of exhaust treatment systems [13, 14]. Analyses of urban crisis periods in Quito and Beirut have demonstrated the formation of localized "hot spots" of elevated $PM_{2.5}$ concentrations in areas with intensive generator use [15, 16]. Similar effects have been described in earlier studies of backup diesel units in urban environments in the United States [17, 18].

According to Ukrainian and international studies, when generators are densely installed, pollutant concentrations in the breathing zone may significantly exceed background levels. At the same time, such peak values are usually not recorded by official stationary monitoring stations, which reflect only the overall urban background [19]. The problem of limited spatial resolution of traditional monitoring systems is emphasized in studies devoted to mobile monitoring and the use of low-cost sensors [20–22]. Such approaches make it possible to detect short-term local exceedances that remain beyond the scope of official systems.

In this context, the application of artificial intelligence methods for the analysis of large environmental datasets becomes particularly relevant. Systematic reviews confirm the effectiveness of machine learning for clustering, anomaly detection, and forecasting air pollution levels [23, 24]. The integration of mobile or local monitoring with AI-based analysis enhances the accuracy of spatial data interpretation and enables the identification of areas of increased environmental risk [21, 25].

Despite the availability of international studies on the impact of diesel generators under crisis conditions, Ukraine lacks systematized instrumental research assessing the actual environmental impact of generators at the level of individual streets or building facades. In particular, there is a shortage of studies combining local field monitoring with spatial data analysis based on artificial intelligence methods. This scientific gap necessitates the implementation of a comprehensive study under conditions of dense urban development.

**The purpose.** The aim of the study is to quantitatively assess the impact of gasoline and diesel power generators on ambient air quality and acoustic load under conditions of dense urban development based on instrumental measurements and AI-based methods for spatial distribution analysis of indicators.

**Materials and methods.** The study was conducted in the central part of the city of Dnipro (Ukraine) along Dmytro Yavornytskyi Avenue between Barykadna Street and Volodymyr Monomakh Street. The selected area is characterized by dense facade development, intensive pedestrian and vehicular traffic, and a high concentration of commercial facilities. During November-December 2025, amid prolonged power outages, gasoline and diesel power generators were systematically operated within the study area, installed directly near the entrances of shops and service establishments along the sidewalks.

To characterize local emission sources, an analysis of the most common generator models used in the city's commercial sector was carried out. The selection of models was based on the analysis of data from Ukrainian marketplaces and the results of field observations during the study period. Among the recorded units, the gasoline generators Hyundai HY3100L and Könner & Söhnen KS 7000E, as well as the diesel generator Matari MDG 6000E, were identified. These models have a rated power of 2.5–5.5 kW, a fuel consumption of 1.2–1.8 L/h, and a noise level of 68–82 dB depending on design features. These units were considered representative sources of local emissions within the study area.

The monitoring scheme involved placing measurement points at 10 m intervals along the façade line of the

avenue, which ensured spatial detailing of pollution distribution within the "street canyon". Measurements were conducted at pedestrian breathing height. Two observation series were organized: during active generator operation (loaded mode) and during their complete shutdown (background conditions). This approach allowed for a direct comparison of the local impact of autonomous sources with baseline urban environmental conditions.

Measurements were carried out using certified mobile instruments capable of recording concentrations of carbon monoxide (CO), nitrogen oxides ($NO_x$), fine particulate matter ($PM_{2.5}$), as well as sound pressure levels in dBA. The following portable laboratory instruments were used for instrumental measurements: the Walcom SR-516A dust analyzer for determining $PM_{2.5}$ concentrations (laser optical light-scattering sensor), the Tenmars TM-801 carbon monoxide gas analyzer (electrochemical sensor), the Tenmars TM-802 formaldehyde gas analyzer, the CEM DT-9881 air quality analyzer, and the AZ-7755 device for monitoring $CO_2$ concentrations. According to the manufacturers' technical specifications, the relative measurement error ranged within ±5–10 % depending on the parameter. The integration time for a single measurement was 30–60 s with recording of the stabilized value. Prior to fieldwork, instrument operability checks and zero-level control were performed.

Primary results of pollutant concentrations were obtained in mg/m$^3$, after which conversion to μg/m$^3$ was performed in accordance with international practice using the following formula

$$PM_{2,5}(\mu g/m^3) = PM_{2,5}(mg/m^3) \cdot 1{,}000. \qquad (1)$$

The obtained values were used for subsequent comparison with national standards and international air quality assessment scales.

Measurements were performed at the microscale in the near-source zone, at a distance of approximately up to 0.5 m from the generator exhaust outlet. Peak concentration values in the exhaust plume were recorded during stable operation of the unit. The obtained values characterize local peak exposure episodes rather than daily average concentrations of the urban background.

Primary data processing included verification of measurement accuracy, elimination of technical artifacts, and formation of a unified observation dataset. To ensure the validity of multivariate analysis, indicator standardization was applied using the z-normalization formula

$$x_{ij}^{*} = (x_{ij} - \mu_j)/\sigma_j,$$

where $x_{ij}$ is the value of the $i^{th}$ indicator at the $i^{th}$ point, and $\mu_j$ and $\sigma_j$ are the mean value and standard deviation of the indicator within the sample, respectively. Such normalization prevented the dominance of individual parameters (in particular, noise) during distance calculations in multidimensional space.

To identify characteristic pollution regimes, the $k$-means algorithm was applied as an unsupervised machine learning method. The number of clusters was selected within the range of $k = 2–3$ depending on the data structure. Clustering was performed using the Euclidean metric in the space of normalized indicators (CO, $PM_{2.5}$, $NO_x$, Noise). This approach enabled the automatic division of observations into groups corresponding to background conditions, local generator impact, and transitional states.

At the second stage of the analysis, anomaly detection (outlier detection) was performed. For each indicator within the background cluster, the mean value and standard deviation were calculated. Observations for which the indicator value exceeded $\mu + 2\sigma$ were considered anomalous episodes of local pollution.

The assessment of non-carcinogenic risk in this study has a screening character. The use of the *RfC*, developed for chronic inhalation exposure, was applied as a conservative approach for the preliminary identification of potentially high-risk zones. Since the recorded concentrations reflect peak short-term exposure episodes in the immediate vicinity of the source, the obtained HQ values should be interpreted as an indicator of potential hazard under conditions of regular repeated exposure rather than as an assessment of daily average or lifetime risk.

Non-carcinogenic risk assessment was performed by calculating hazard quotients using the following formula

$$HQ_i = C_i/RfC,$$

where $HQ_i$ is the hazard quotient for the $i^{th}$ substance; $C_i$ is the actual concentration; *RfC* is the safe exposure level. The integral non-carcinogenic risk index (HI) was determined as the sum of HQ values for all studied pollutants. This approach made it possible to integrate the results of instrumental measurements into a quantitative framework for assessing potential health impacts on the population.

**Results and discussion.** The actual presence of power generators on shop facades during November–December 2025 confirms their representativeness as local emission sources within the studied section of Dmytro Yavornytskyi Avenue. The spatial placement of generators directly within the pedestrian zone creates conditions for the formation of localized areas of elevated pollutant concentrations in the near-ground air layer.

Further analysis focused on comparing the results of instrumental monitoring under background and loaded conditions in order to quantitatively assess the impact of these sources on ambient air quality and acoustic load levels.

Within the studied section with a length of 624.5 m, up to 15 autonomous gasoline and diesel generators were recorded operating simultaneously during peak periods. Emission sources were located directly near the entrances of commercial facilities at a height of 0.5–1.5 m above the sidewalk surface, corresponding to the pedestrian breathing zone. Most units were operated without additional noise protection screens or exhaust gas treatment systems. Considering the morphology of the built environment (dense façade line, limited sidewalk width, and the "street canyon" effect), conditions were created for the local accumulation of pollutants and increased acoustic load levels (Figs. 1, 2).

Field instrumental measurements of CO, $PM_{2.5}$, $NO_x$ concentrations and sound pressure levels during active generator operation are presented in Table 1. The obtained values reflect the actual level of local anthropogenic load within the studied section under emergency power supply conditions.

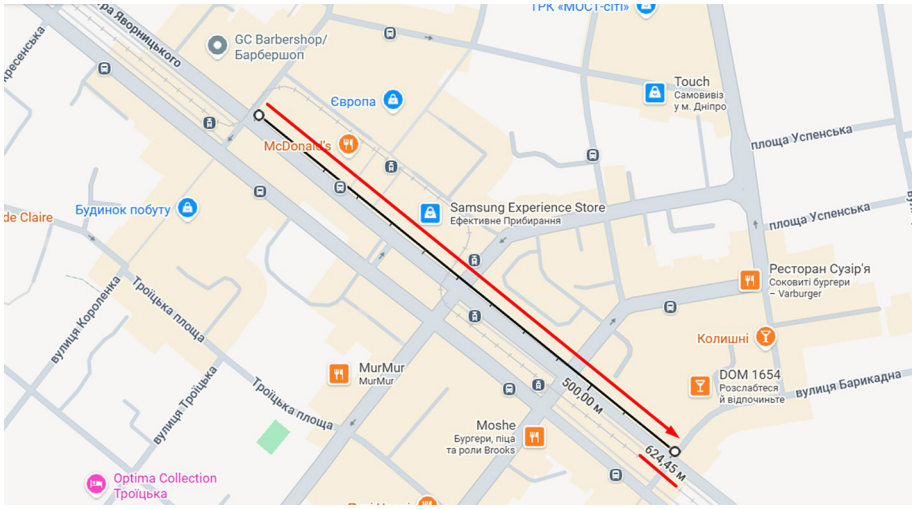


*Fig. 1. Spatial layout of the studied section along Dmytro Yavornytskyi Avenue (Dnipro) indicating the route of instrumental monitoring (total length — 624.5 m)*

*Fig. 2. Spatial distribution of autonomous generators within the street canyon along Dmytro Yavornytskyi Avenue (Dnipro, Ukraine)*

*Table 1*

Instrumental indicators of air quality and noise levels during active generator operation

| Measurement point | CO, mg/m$^3$ | PM, mg/m$^3$ | $NO_x$, mg/m$^3$ | Noise, dBA | Maximum permissible level | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | CO, mg/m$^3$ | $PM_{2.5}$, mg/m$^3$ | $NO_x$, mg/m$^3$ | Noise, dBA |
| Point 1 | 5.2 | 0.68 | 0.2 | 71 | 5.0 | 0.5 | 0.2 | 65 |
| Point 2 | 4.7 | 0.62 | 0.18 | 74 | 5.0 | 0.5 | 0.2 | 65 |
| Point 3 | 6.1 | 0.73 | 0.26 | 76 | 5.0 | 0.5 | 0.2 | 65 |
| Point 4 | 5.5 | 0.66 | 0.22 | 75 | 5.0 | 0.5 | 0.2 | 65 |
| Point 5 | 4.9 | 0.59 | 0.19 | 71 | 5.0 | 0.5 | 0.2 | 65 |

The analysis of the obtained results indicates exceedances of regulatory levels for most of the studied parameters. CO concentrations exceeded the maximum permissible value of 5.0 mg/m$^3$ at Points 1, 3, and 4, reaching a maximum of 6.1 mg/m$^3$ at Point 3. This corresponds to an exceedance of 22 % relative to the standard.

$PM_{2.5}$ concentrations at all measurement points exceeded the permissible level of 0.5 mg/m$^3$, ranging from 0.59 to 0.73 mg/m$^3$, which corresponds to exceedances of 18–46 %. The highest concentration was recorded at Point 3, indicating the formation of a local accumulation zone of fine particulate matter.

For $NO_x$, exceedances of the regulatory value of 0.2 mg/m$^3$ were recorded at Points 1, 3, and 4. The highest level (0.26 mg/m$^3$) at Point 3 exceeds the permissible value by 30 %, indicating a significant contribution from incomplete fuel combustion processes.

Noise levels exceeded the regulatory limit of 65 dBA at all measurement points, ranging from 71 to 76 dBA. The maximum value of 76 dBA exceeds the permissible level by 11 dBA, which is significant from the perspective of sanitary standards.

Thus, Point 3 is characterized by simultaneous peak increases in all studied parameters, allowing it to be identified as a local center of maximum impact from autonomous power sources.

The measurement results during the period of complete generator shutdown are presented in Table 2.

After the shutdown of the generators, a significant decrease in pollutant concentrations was observed. CO

*Table 2*

Instrumental indicators of air quality and noise levels under background conditions

| Measurement point | CO, mg/m³ | PM, mg/m³ | $NO_x$, mg/m³ | Noise, dBA | Maximum permissible level | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | CO, mg/m³ | $PM_{2.5}$, mg/m³ | $NO_x$, mg/m³ | Noise, dBA |
| Point 1 | 3.4 | 0.57 | 0.19 | 61 | 5.0 | 0.5 | 0.2 | 65 |
| Point 2 | 4.1 | 0.49 | 0.18 | 62 | 5.0 | 0.5 | 0.2 | 65 |
| Point 3 | 5.3 | 0.56 | 0.22 | 61 | 5.0 | 0.5 | 0.2 | 65 |
| Point 4 | 5.0 | 0.44 | 0.2 | 59 | 5.0 | 0.5 | 0.2 | 65 |
| Point 5 | 4.3 | 0.48 | 0.17 | 60 | 5.0 | 0.5 | 0.2 | 65 |

concentrations decreased to 3.4–5.3 mg/m³. At most points, the values approached the regulatory level or remained within permissible fluctuations. $PM_{2.5}$ concentrations decreased to 0.44–0.57 mg/m³, which in some points still exceeds the standard, possibly due to the influence of traffic flow and secondary dust resuspension. Noise levels decreased to 59–62 dBA, corresponding to or slightly exceeding the regulatory limits.

To quantitatively assess the impact of generators, the relative reduction of indicators between the two observation phases was calculated (Table 3).

The greatest relative reduction was recorded for CO (up to 35 %) and noise (up to 21 %). The decrease in $PM_{2.5}$ concentrations ranged from 16 to 33 %, indicating a significant contribution of generators to the formation of fine particulate matter load. The dynamics of $NO_x$ were less pronounced, which may be explained by background traffic influence.

The obtained results confirm the substantial contribution of autonomous gasoline and diesel generators to the formation of localized zones of increased chemical and acoustic load within dense urban development.

To ensure comparability of the obtained results with European approaches to ambient air quality assessment, the analysis was additionally performed using $PM_{2.5}$ as a key indicator of aerosol load. The selection of this particle fraction is conditioned by its high penetration capacity into the respiratory tract and its proven role in the formation of non-carcinogenic health risks.

Since the primary field measurement results were obtained in mg/m³, they were converted to μg/m³ in accordance with international practice for reporting atmospheric aerosol concentrations. The conversion was performed using the following formula (1).

The obtained $PM_{2.5}$ values were compared with the threshold intervals of the European Environment Agency (EEA) scale as a tool for indicative interpretation of pollution levels. At the same time, it should be noted that the measurements were performed at the microscale near the emission source (exhaust plume zone) and reflect short-term peak concentrations, whereas the EEA scale is based on averaged ambient air quality indicators [26]. Therefore, this comparison has a screening character and is used for preliminary classification of the level of local impact rather than as a full regulatory assessment based on an equivalent averaging period.

Based on this approach, each observation point was classified with the determination of the corresponding air quality category and environmental risk level within the studied section (Table 4).

As shown by the results in Table 4, $PM_{2.5}$ concentrations corresponding to the highest pollution class according to the EEA scale (Class 5 – "very poor") were recorded at all control points. The actual peak values significantly exceed the threshold intervals corresponding to the worst category of the EEA scale, indicating the formation of zones of critical local aerosol load in the immediate vicinity of the emission source within the pedestrian space.

Considering the linear arrangement of generators and the morphology of the street space (dense facade development, limited air ventilation under "street canyon" conditions), the recorded concentrations may be regarded as the result of local accumulation of emissions in the near-ground atmospheric layer. The spatial uniformity of high $PM_{2.5}$ values across all observation points indicates a systemic rather than random impact of autonomous power sources.

Thus, classification according to the EEA scale made it possible to quantitatively confirm the high level of environmental load and to demonstrate the consistency of the obtained data with international approaches to air quality assessment.

Given that during scheduled and emergency outages generators operate in one or two shifts for 6–8 hours, which constitutes a substantial part of the day, and have maintained a stable operating period in recent years, they can be considered quasi-stationary sources of atmospheric air pollution. In addition, during instrumental monitoring, variations in $PM_{2.5}$, CO, and $NO_2$ concentrations near generators did not exceed 20–35 % within a 20-minute interval. Therefore, for the purpose of quantitatively assessing the potential impact of the re-

*Table 3*

Relative change in pollutant concentrations and noise levels after generator shutdown (%)

| Parameter | Point 1 | Point 2 | Point 3 | Point 4 | Point 5 |
|---|---|---|---|---|---|
| CO, % | ↓35 | ↓13 | ↓13 | ↓9 | ↓12 |
| $PM_{2.5}$, % | ↓16 | ↓21 | ↓23 | ↓33 | ↓19 |
| $NO_x$, % | ↓5 | ↓0 | ↓15 | ↓9 | ↓11 |
| Noise, % | ↓14 | ↓16 | ↓20 | ↓21 | ↓15 |

*Table 4*

Air quality assessment based on $PM_{2.5}$ according to the EEA classification

| Point | $PM_{2.5}$, mg/m³ | $PM_{2.5}$, μg/m³ | EEA class | Risk level |
|---|---|---|---|---|
| 1 | 0.68 | 680 | 5 (Very poor) | Critical |
| 2 | 0.62 | 620 | 5 (Very poor) | Critical |
| 3 | 0.73 | 730 | 5 (Very poor) | Critical |
| 4 | 0.66 | 660 | 5 (Very poor) | Critical |
| 5 | 0.59 | 590 | 5 (Very poor) | Critical |

corded pollutant concentrations on public health, non-carcinogenic risk can be determined in accordance with the WHO inhalation exposure assessment methodology. This approach allows a transition from comparison with regulatory values to the determination of individual hazard quotients for each component and an integral indicator of combined exposure.

Hazard quotients (HQ) were calculated based on the ratio of actual pollutant concentrations to reference exposure levels. Additionally, the hazard index (HI), characterizing the cumulative effect of simultaneous inhalation of several substances, was determined. An HQ value > 1 is considered an indicator of potential risk of developing non-carcinogenic effects.

The results of the calculations of hazard quotients and the integral HI index for the control points of the studied section are presented in Table 5.

The analysis of hazard quotient (HQ) calculations indicates substantial variability in individual risks for specific components. The highest HQ values were recorded for fine particulate matter $PM_{2.5}$ (*HQ* = 39.3–48.6), indicating the dominant contribution of the aerosol fraction to the formation of non-carcinogenic risk. For nitrogen oxides, HQ values ranged from 4.5 to 6.5, whereas for carbon monoxide they ranged from 1.6 to 2.0.

The obtained results indicate the formation of conditions of combined inhalation load, which may be considered potentially adverse to public health under conditions of regular exposure.

Considering the nature of the identified exceedances, the most sensitive body systems under such exposure are the respiratory system, the immune system, and the central nervous system, which is consistent with the known mechanisms of toxic effects of the studied substances.

At the same time, it should be noted that the applied methodology allows for the assessment of potential risk levels based on pollutant concentrations but does not provide for the prediction of specific clinical outcomes for the population. The obtained values reflect the relative level of hazard under inhalation exposure conditions and are used for comparative assessment of environmental load.

To convert concentration values into risk indicators of acute reflex effects in the population, the following equations may be applied [25], taking into account the hazard class of the pollutant (3–6)

$$\text{class 1} - Prob = -9.15 + 11.66 \cdot \log(C_i/MPC_{m.r.});$$

$$\text{class 2} - Prob = -5.51 + 7.49 \cdot \log(C_i/MPCm.r.);$$

$$\text{class 3} - Prob = -2.35 + 3.73 \cdot \log(C_i/MPC_{m.r.});$$

$$\text{class 4} - Prob = -1.41 + 2.33 \cdot \log(C_i/MPC_{m.r.}),$$

where $C_i$ is the concentration of the substance to which the population is exposed; *MPC* (one-time) is the maximum permissible one-time concentration; *Prob* is a value associated with risk according to the normal distribution law. In this case, the probit (*Prob*) and probability (*Risk*) are related through a tabulated integral

$$Risk = (1/\sqrt{(2\pi)}) \int_{-\infty}^{Prob} e^{(-t^2/2)} dt.$$

The results of the assessment of the risk of acute effects are presented in Table 6

Thus, the risk of acute reactions resulting from atmospheric air pollution by carbon monoxide and dust emissions from generators is satisfactory under conditions of short-term exposure to the specified concentrations. An equally important task is the assessment of the dynamics of pollutant concentrations before and after generator shutdown, as well as the measurement of their concentrations at different distances in order to study dispersion processes in the ambient air.

Table 7 and Fig. 3 present the dynamics of pollutant concentrations from emissions of the gasoline generator KD162 Kraft&DFK Pro 212cc and the diesel generator

*Table 5*

Analysis of non-carcinogenic risks for damage to critical organs

| Substance | Concentration, mg/m³ | RfC, mg/m³ | HQ | Critical organs |
|---|---|---|---|---|
| $PM_{2.5}$ | 0.59–0.73 | 0.015 | 39.3–48.6 | Respiratory system |
| CO | 4.7–6.1 | 3 | 1.6–2.0 | CNS, cardiovascular system, blood |
| $NO_2$ | 0.18–0.26 | 0.04 | 4.5–6.5 | Respiratory system |
| Total non-carcinogenic risk | | Respiratory system | 43.8–55.1 | |
| | | CNS, cardiovascular system, blood | 1.6–2.0 | |

*Table 6*

Calculation of the probability of acute reactions according to hazard classes of substances

| Substance | Concentration, mg/m³ | $MPC_{m.r}$ | Hazard class | Value of risk of acute reactions | Assessment of risk of acute reactions | Criteria for risk of acute reactions |
|---|---|---|---|---|---|---|
| CO | 6.1 | 5 | 4 | 0.113 | Satisfactory | Various discomfort conditions may occur; background morbidity level |
| Dust | 0.73 | 0.5 | 3 | 0.041 | Satisfactory | Various discomfort conditions may occur; background morbidity level |
| $NO_2$ | 0.26 | 0.2 | 2 | 0.001 | Acceptable | Background morbidity level of the population associated with inhalation and oral exposure to a non-carcinogen; discomfort in isolated cases among particularly sensitive individuals |

*Table 7*

Spatial distribution of pollutant concentrations depending on the distance from the generator

| Distance, m | Carbon monoxide | | $PM_{2.5}$ | | Formaldehyde | | Carbon dioxide | |
|---|---|---|---|---|---|---|---|---|
| | mg/m³ | MPC (daily average) | μg/m³ | MPC (daily average) | mg/m³ | MPC (daily average) | μg/m³ | MPC (daily average) |
| 1 | 5.10 | 1.70 | 326.00 | 3.26 | 0.10 | 33.33 | 630.00 | 1.26 |
| 2 | 5.00 | 1.67 | 225.00 | 2.25 | 0.05 | 16.67 | 512.00 | 1.02 |
| 4 | 3.60 | 1.20 | 149.00 | 1.49 | 0.03 | 10.00 | 520.00 | 1.04 |
| 6 | 4.20 | 1.40 | 95.00 | 0.95 | 0.01 | 3.33 | 511.00 | 1.02 |
| 8 | 3.10 | 1.03 | 84.00 | 0.84 | 0.00 | 1.33 | 497.00 | 0.99 |
| 10 | 2.30 | 0.77 | 65.00 | 0.65 | 0.01 | 1.67 | 500.00 | 1.00 |

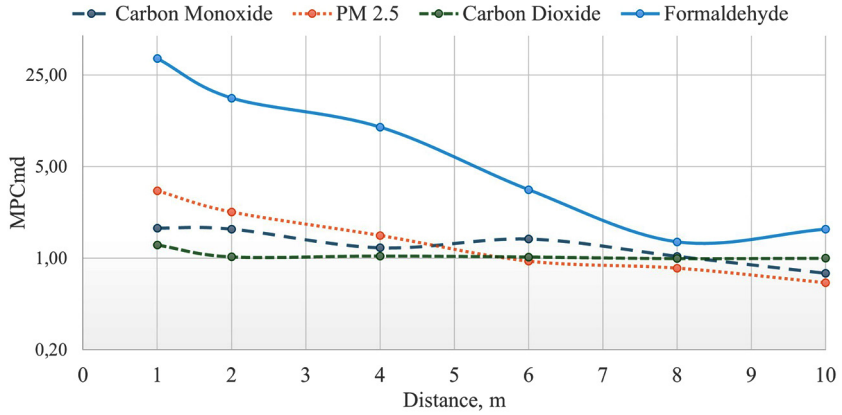


*Fig. 3. Spatial gradient of* CO, $PM_{2.5}$, *formaldehyde, and* $CO_2$ *concentrations depending on the distance from the emission source*

K&S BASIC KS 8000 DE-3 498cc during their synchronous operation at nominal power.

As can be seen, among all the measured pollutants, the highest concentration values were identified for formaldehyde, reaching up to 0.10 mg/m³, which is 33 times higher than the MPC (daily average) directly near the generators. The concentration decreased with increasing distance from the operating generators; however, even at a distance of 10 m it still exceeded the regulatory limit. It should be noted that elevated formaldehyde levels are generally characteristic of the city of Dnipro, particularly during the hot season. The remaining pollutants exhibited lower exceedances of the daily average MPC and decreased to permissible levels at a distance of 6–8 m from the operating generators, which can be considered a safe distance from the perspective of atmospheric air pollution by exhaust emissions.

To identify spatial patterns of pollution distribution and determine typical risk zones, further analysis was performed using artificial intelligence and machine learning methods [23, 24].

In addition to traditional statistical analysis, artificial intelligence tools were applied, allowing a transition from a descriptive approach to automated detection of spatial pollution patterns. The structural scheme of the data processing algorithm is presented in Fig. 4.

As input data for the AI-based analysis, the results of instrumental measurements of CO, $PM_{2.5}$, $NO_x$ concentrations and noise levels were used, obtained under two operational conditions:

- active operation of generators (ON mode);
- absence of generator operation (background conditions, OFF mode).

For each monitoring point, a feature vector was constructed

$$x_i = (CO_i, PM_{2,5i}, NO_{xi}, Noise_i, d_i, m_i),$$

where $d_i$ denotes the distance from the nearest generator to the measurement point, and $m_i$ is a binary mode indicator (1 – generators operating, 0 – generators switched off).

Such an approach allows accounting for both the physical environmental parameters and the operational mode of the emission source [27].

Since the indicators are measured in different units (mg/m³, dBA, meters), the data were standardized prior to the application of machine learning algorithms using z-score normalization

$$z_{ij} = (x_{ij} - \mu_j)/\sigma_j,$$

where $x_{ij}$ denotes the value of the $j^{th}$ feature at the $i^{th}$ observation point, and $\mu_j$ and $\sigma_j$ represent the mean and standard deviation of the corresponding feature across the sample.

Such normalization prevents certain parameters (e.g., noise levels) from dominating the Euclidean distance metric during clustering [24].

Additionally, the dataset was checked for missing values and outliers. When necessary, isolated missing values were interpolated using neighboring points, while clearly artifact values (associated with instrumental malfunction) were excluded from further analysis.

To identify *characteristic "pollution regimes"*, the *k*-means algorithm was applied as a fundamental unsupervised learning method widely used in the analysis of urban air pollution structures and VOC/$NO_x$ profiles [25].

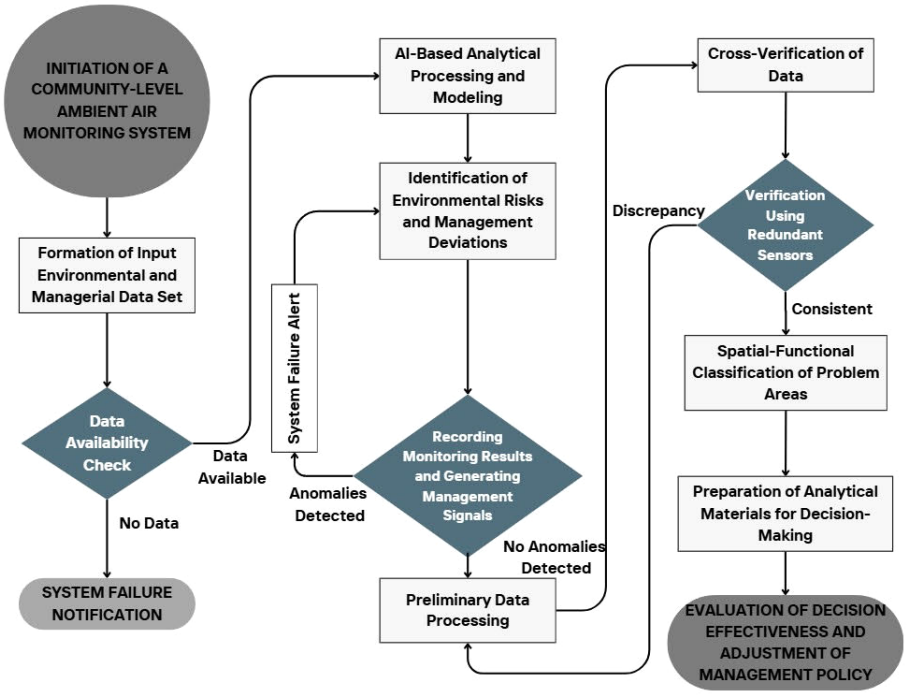


*Fig. 4. Algorithm of AI-Based analysis and data reliability control in ambient air monitoring*

Within the study, models with $k = 2–3$ clusters were examined:

Cluster 1 – background conditions (low CO, $PM_{2.5}$, $NO_x$ concentrations and lower noise levels);

Cluster 2 – local load from generators (elevated CO and $PM_{2.5}$ concentrations, increased noise, short distance to the generator);

Cluster 3 – transitional/mixed states (e.g., when some generators are already switched off, but traffic intensity remains high).

The optimal number of clusters was determined using within-cluster dispersion analysis (the elbow method). As $k$ increased, the total sum of squared errors gradually decreased; however, beyond $k = 3$, the rate of reduction significantly slowed, indicating the appropriateness of a three-cluster structure.

Clustering quality was additionally assessed using the silhouette coefficient, which confirmed a sufficient level of separation between observation groups. Increasing $k$ beyond 3 did not substantially improve data structure; therefore, $k = 3$ was adopted as the optimal value for further interpretation.

Clustering enables:

- formal separation of observations into "background – generator impact" groups without applying a manual threshold;
- identification of typical pollution profiles for subsequent public health risk assessment;
- construction of cluster-based maps along the avenue, where color coding represents the regime assignment of each point.

At the second stage, anomaly detection (outlier detection) was performed based on the clustering results. For each parameter $p \in \{CO, PM_{2.5}, NO_x, Noise\}$ within the background cluster, the mean value ($\mu_p^{background}$) and standard deviation ($\sigma_p^{background}$) were calculated. Observations for which are

$$x_{ip} > \mu_p^{bg} + 2\sigma_p^{bg}.$$

Observations exceeding the established threshold are classified as anomalously high values and interpreted as peak local pollution events associated with the operation of one or multiple generators in the vicinity of the measurement point [25].

The proposed approach enables:

- quantitative detection of pollution peaks relative to baseline urban conditions;
- estimation of the share of anomalous observations for each monitored parameter;
- spatial attribution of peak episodes to specific avenue segments and generator spatial configurations.

The outputs of clustering and anomaly detection are incorporated into the integrated risk assessment model, forming the analytical basis for spatial differentiation of exposure levels and identification of priority intervention zones:

1. Instrumental stage: measurement of CO, $PM_{2.5}$, $NO_x$ concentrations and noise levels under two operational modes (generators ON/OFF).
2. Data normalization and feature matrix construction.
3. Clustering ($k$-means): identification of background and generator-related pollution regimes.
4. Anomaly assessment: identification of peak episodes, their frequency, and spatial distribution.
5. Interpretation for risk assessment:

- comparison of mean and peak values with maximum permissible concentrations (MPC);
- qualitative interpretation of the identified clusters as risk scenarios for individuals located along the avenue (shop employees, pedestrians).

Such an approach allows substantiated conclusions not only regarding isolated exceedances of maximum permissible concentrations (MPC), but also concerning the structure and intensity of local pollution regimes specifi-

cally associated with generator use. Conceptually, it aligns with contemporary studies in which AI techniques are applied to identify pollution regimes, forecast air quality, and support environmental policy decision-making.

The resulting cluster structure demonstrates clear environmental interpretability and reflects the spatial stratification of autonomous generator impacts on air quality and acoustic load.

Cluster K1 is characterized by relatively lower concentrations of $PM_{2.5}$ and CO, as well as reduced noise levels, corresponding to weakened or background emission influence. These points are typically located at greater distances from generators or within zones of partial pollutant dispersion.

Cluster K2 exhibits consistently elevated concentrations of fine particulate matter and increased noise levels, indicating localized anthropogenic load. These points are generally situated in close proximity to operating generators or within street canyon environments characterized by limited ventilation.

Cluster K3 corresponds to zones of maximum chemical and acoustic impact. It is characterized by the highest values across all monitored parameters, allowing its interpretation as an area of critical environmental load.

Thus, the application of the *k*-means algorithm enabled not only formal grouping of observations but also quantitative confirmation of distinct local pollution regimes associated with autonomous energy sources. The identification of clusters provides a basis for subsequent public health risk assessment and spatial typology of areas according to environmental hazard levels.

As a result of the analysis, the observations were distributed into clusters K1–K3 (Table 8).

**Conclusions.** The study involved a field-based instrumental assessment of the impact of autonomous gasoline and diesel generators on ambient air quality and acoustic load under conditions of dense urban development in the central part of the city of Dnipro. It was established that the simultaneous operation of approximately 15 generators along a 624.5 m section results in the formation of localized zones of elevated chemical and acoustic load within the pedestrian space.

During the period of active generator operation, exceedances of regulatory levels were recorded for CO (up to 6.1 mg/m$^3$), $PM_{2.5}$ (up to 0.73 mg/m$^3$), and noise (up to 76 dBA). $PM_{2.5}$ concentrations at all monitoring points corresponded to the worst air quality category according to the EEA scale (>50 μg/m$^3$), exceeding the threshold level by 12–15 times. Comparative analysis of the "generators ON/OFF" regimes demonstrated reductions of up to 35 % for CO, 33 % for $PM_{2.5}$, and 21 % for noise, confirming the dominant contribution of autonomous power sources to local pollution formation.

*Table 8*

Results of cluster analysis of monitoring points based on pollutant concentrations and noise levels

| Cluster | Points | Characteristics | Risk Level |
|---|---|---|---|
| K1 | Points 2, 5 | Relatively lower values of $PM_{2.5}$, noise, and gaseous pollutants | Elevated |
| K2 | Points 1, 4 | Consistently elevated concentrations of $PM_{2.5}$ and noise levels | High |
| K3 | Point 3 | Maximum values across all monitored indicators | Critical |

Non-carcinogenic risk assessment revealed exceedances of hazard quotients for $PM_{2.5}$ and $NO_x$, while integrated hazard indices for the respiratory system significantly exceeded the threshold value, indicating the dominant contribution of the aerosol fraction to overall risk formation.

For the first time under conditions of Ukrainian urban development, the feasibility of applying machine learning algorithms (*k*-means clustering and anomaly detection) for automated typology of local pollution risk zones associated with autonomous power sources has been demonstrated. Cluster analysis enabled the identification of background, elevated, and critical pollution regimes, thereby expanding the capacity for operational assessment of urban environmental load.

The obtained results highlight the necessity of integrating mobile monitoring systems and intelligent data processing into the structure of urban environmental control systems. Further research should focus on expanding the dataset, incorporating meteorological parameters, and developing predictive models of pollutant dispersion within street canyons.

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## Інструментальний моніторинг забруднення повітря від генераторів з елементами AI-аналізу даних: методика й оцінка ризиків

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**Мета.** Інструментальна оцінка впливу електрогенераторів на якість атмосферного повітря й акустичне навантаження у центральній частині міста Дніпро, а також тестування елементів штучного інтелекту для аналізу просторового розподілу забруднюючих речовин.

**Методика.** Серія польових вимірювань рівнів чадного газу (CO), оксидів азоту ($NO_x$), твердих частинок (PM) і шуму була проведена на стаціонарних точках моніторингу вздовж проспекту Дмитра Яворницького у фонових умовах і під час роботи генератора. Обробка даних включала статистичний аналіз, нормалізацію показників і кластеризацію з використанням методів машинного навчання для виявлення просторових закономірностей і варіацій концентрацій забруднюючих речовин та акустичних рівнів.

**Результати.** Дослідження виявило формування локалізованих зон підвищеного забруднення повітря й підвищеного акустичного навантаження в безпосередній близькості від працюючих генераторів. Під час роботи генератора були зафіксовані підвищені концентрації CO, $NO_x$ і PM, а також вищі рівні шуму порівняно із фоновими умовами. Аналіз на основі штучного інтелекту дозволив диференціювати зони з різним ступенем екологічного ризику в межах досліджуваної міської території.

**Наукова новизна.** Уперше розроблена й апробована інтегрована методика оцінки кумулятивного екологічного ризику в умовах екстремально високої щільності автономних джерел живлення (до 24 агрегатів на 1 км фасадної лінії) у специфічній морфології «вуличного каньйону». Наукову новизну представляють встановлені закономірності формування локальних «гарячих точок» (hotspots) забруднення, де концентрації $PM_{2.5}$ перевищують міжнародні нормативи EEA у 12–15 разів. Запропоновано новий підхід до верифікації техногенного навантаження через алгоритм *k*-means кластеризації, що дозволяє диференціювати внесок генераторів від загальноміського фону із точністю, недоступною для стаціонарних постів моніторингу.

**Практична значимість.** Отримані результати можуть бути використані для розробки рекомендацій щодо розміщення електрогенераторів у міському середовищі й для вдосконалення локальних систем моніторингу навколишнього середовища в умовах аварійного електропостачання. На основі встановлених закономірностей розсіювання (зниження концентрацій у 1,5–2 рази на відстані 4–6 метрів) рекомендовано встановлення мінімальної дистанції розміщення генераторів від ліній дихання пішоходів і входів до будівлі не менше 5 метрів, а також обов'язкове використання вертикальних відвідних труб вихлопу висотою понад 2,5 метри для виходу газів за межі приземного шару

**Ключові слова:** *генератор, якість повітря, шум, урбанізовані території, штучний інтелект, екологічна безпека*