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# Quantifying the impact of meteorological factors and green infrastructure location on particulate matter (PM) mitigation in Republic of North Macedonia using sensor collected data

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ABSTRACT

Low quality of the air is becoming a major concern in urban areas. High values of particulate matter (PM) concentrations and various pollutants may be very dangerous for human health and the global environment. The challenge to overcome the problem with the air quality includes efforts to improve healthy air not only by reducing emissions, but also by modifying the urban morphology to reduce the exposure of the population to air pollution.

The aim of this contribution is to analyse the influence of the green zones on air quality mitigation through sensor measurements, and to identify the correlation with the meteorological factors. Actually, the objective focuses on identifying the most significant correlation between PM2.5 and PM10 concentrations and the wind speed, as well as a negative correlation between the PM concentrations and wind speed across different measurement locations. Additionally, the estimation of slight correlation between the PM concentrations and the real feel temperature is detected, while insignificant correlations are found between the PM concentrations and the actual temperature, pressure, and humidity.

In this paper the effect of the pandemic restriction rules COVID-19 lockdowns and the period without restriction are investigated. The sensor data collected before the pandemic (summer months in 2018), during the global pandemic (summer months 2020), and after the period with restriction measures (2022) are analysed.

## 1. Introduction

Air pollution is among the highest environmental risks impacting human health. Major air pollutants in cities include PM, sulphur dioxide ($SO_2$), carbon monoxide (CO), ozone ($O_3$), nitrogen oxides ($NO_X$), and volatile organic compounds (VOCs) [1]. Research presented in Refs. [2,3] shows increased rates of death associated with increased air pollutants concentration (such as $O_3$, PM and $SO_2$). According to the report presented in Ref. [4], air pollution is a major cause of death in many European countries, and the cause for more than 400,000 premature deaths. Except for human health, these pollutants can be a serious danger to monuments and artwork, especially the memorials located in the city centres [5].

The impact of air pollution is the highest in urban environments. Global urbanisation and construction of new buildings in big cities lead to temperature increase and consequently, in air pollution increase [6,7]. This phenomenon known as urban heat island (UHI) effect has been studied by lot of authors. In the paper presented by Ref. [8] the city temperature can rise by 2 °C–8 °C, while according to newer research [9] the city temperature rise can be between 5 °C and 15 °C. In the paper presented by Grimmond [10], it is estimated that by 2030, 61% of the world's population would inhabit cities, and the UHI effect would be more intensive as a result of deforestation and global warming. In order to overcome the urban environmental problems some authors have analysed the effects of vegetation, particularly trees, on cooling urban air, shading buildings and absorbing gaseous air contaminants [11,12]. A simple and innovative approach considers implementation of green walls, green facades and green buildings for air pollution mitigation. The effectiveness of such approach has been confirmed in various cases applied in Switzerland, Sweden UK, USA, Spain [13]. Some of the

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benefits of the implementation of vertical green walls and green roof surfaces on building facades include improvement of the thermal characteristics of the objects, reduction of the noise level as well as reduction of the energy requirements of the facilities [14]. The impact of vegetation on the thermal environment of buildings was examined in the studies of [15,16]. Huang [17] quantified that by using green roofs in Tokyo and showed that the average ambient temperature can be lowered by 0.3 °C, while in the work presented by Ref. [18], the estimate of the temperature was 0.1 °C lower. The research presented in Ref. [11] conducted a study to determine the effect of tree planting and re-roofing on ambient temperatures and air pollution. The experiments derive that the ambient temperature can be lower by up to 3 °C and the air around the building can be cooler by implementing trees combined with cool roofs. [19] Similarly looked into the effect of garden roofs on tempering air temperatures. It was concluded that garden roofs are more effective in heat gain reduction in summer than heat loss in winter. The air pollution mitigation by implementation of green walls and green roofs was investigated in the work of [20]. In the paper presented by Ref. [21] different arrangements of trees on pollution dispersion were evaluated. Authors in Ref. [22] suggested Computational fluid dynamics (CFD) model for predicting the pollutant level and its distribution. The model was validated by a test case on a wind tunnel urban canyon in Belgium. They used wind catchers to increase the dispersion process of air pollution removal. Similarly, the study [23] evaluated the ability of an artificial neural network (ANN) algorithm to predict hourly air pollutant concentrations and two air quality indices for Ahvaz, Iran over one full year. The algorithm achieved a correlation coefficient and root-mean square error of 0.87 and 59.9 respectively, demonstrating its applicability for cities such as Ahvaz to forecast air quality and prevent adverse health effects. Another work [24] focuses on data including meteorological parameters, visibility and particulate matter mass concentrations to determine whether there are any meteorological parameters that can be used to predict dust storms. An ANN approach was applied and had strong forecasting skill ($R_2 = 0.71$) for the maximum 3h mean PM10 concentration during dusty days, suggesting that dew point temperature may be used to predict dust storms.

In this context, PM concentrations are directly affected by meteorological parameters such as temperature, wind, precipitation [25,26]. For example, winds reduce the concentration of the particulates (PM2.5 and PM10) as the winds help the particulates stick to the leaves and stems of the plants [27]. The research presented by Refs. [28,29] shows that the green area mitigates the fine particles, with an aerodynamic diameter lower than 2.5 μm (PM2.5) on average by 25% and PM with an aerodynamic diameter lower than 10 μm (PM10) on average by 37% compared to the neighbouring non-green areas. The results show a strong correlation between PM2.5 and PM10, while the combination of low temperatures, high humidity and no, or low wind speed lead to high PM concentrations. The results presented in Ref. [30] show that the weather information parameters such as wind, temperature and humidity are correlated with air pollution, which allows to develop a machine learning air pollution model based on weather information and historical measurement data on the pollution.

An essential element in evaluation of the various methods for air pollution reduction is the possibility to measure, collect and analyse data. The different environments and methods require adequate measurement systems which provide reliable results. For the purpose of the research presented in this paper, an air quality measurement system consisted of wireless sensor nodes (WSNs) is implemented. Each sensor node includes a power unit, sensors for different gaseous pollutants measurement, a microprocessor and a transceiver. The air quality monitoring system is developed as a low - cost and energy - efficient replicable system, confirmed in the analyses presented in Refs. [28,29, 31] which consider its implementation, replication and the consumption of the WSNs.

This paper focuses on the estimation of the impact of the relative position of the measurement sensors and the disposition of the green zones. The investigations also provide analysis on the influences of meteorological factors, such as wind speed and direction, relative humidity, and temperature on PM mitigation. The analyses are based on measurement data, and argumented prognosis showing which parameter has the highest influence on the PM concentrations.

## 2. Background research

The lockdown response to coronavirus disease 2019 (COVID-19) has caused reduction in global economic and transport activity. Reduced mobility and lockdown measures implemented across the world are considered to have helped in air quality improvement. However, there is no empirical equation that connects public mobility changes and air pollution during the COVID-19 period. As presented further in the text, the findings in most of the studies indicate that reducing unnecessary outdoor mobility should help in maintaining air quality in the post-pandemic world.

### 2.1. *Meteorological factors impact on COVID-19 spread and effects*

More influence of the transmission of COVID-19 has been detected in regions with cold and dry temperature conditions, where winters are cool, while summers are wet and warm (Southeast region of the U.S. and large parts of China, Brazil and Argentina). Studies conducted in Singapore, India and China have found a positive relationship between temperature and daily reported cases of COVID-19 virus [32], while positive link between temperature, relative humidity, absolute humidity and wind speed on one side and COVID-19 on the other side were detected in the studies explored in Thailand [33] and Turkey [34]. Similarly, authors in the study [35] looked at the incidence of COVID-19 in the Petroleum Hospital of Ahvaz, Iran between March 2020 and March 2021. The results showed that a high daily air temperature and relative humidity reduced the daily incidence of COVID-19. A negative correlation was detected between COVID-19 cases and air temperature and relative humidity.

A review presented by Mecenas [36] indicated that wet and warm climates reduced the COVID-19 spreading. The studies conducted in China [37] and Indonesia [38] also concluded that lower rates of COVID-19 were associated with high values of the temperature and humidity. In the paper investigated by Christophi et al. [39], they have reported that a 10 °C increase in the ambient temperature resulted in 6% decrease in COVID-19 mortality rates at 30 days after the first reported death. Furthermore, epidemiological data showed that 1 °C temperature increase was associated with a statistically significant 3% decrease in daily COVID-19 cases, while a 1% relative humidity increase was associated with a 0.5% decrease in daily new COVID-19 deaths in 166 countries [40]. Similarly, in the study presented by Liu [19], it was concluded that 1 °C ambient temperature increase was associated with less daily confirmed cases in 17 cities in China. While the study examined in Brazil [41], confirmed negative linear relationship within the range of 16.8–27.4 °C associated with higher temperature on one side and daily confirmed COVID-19 cases on the other side.

The survey examined in U.S countries showed that low air temperature, specific value of humidity and UV radiation were associated with increased number of SARS-CoV-2, while cold and dry weather and low UV radiation levels were fairly connected with coronavirus transmission [42]. While some of the above mentioned studies showed some relationship between the meteorological parameters and COVID-19 rate, in others no such relationship was found.

### 2.2. *The effect of COVID-19 on air pollution*

As presented in this section, it can be concluded that during the pandemic COVID-19 lockdowns, the air pollution was drastically reduced [43]. The pandemic has caused reduced air pollution as the public transportation has been cancelled in many cases, airlines have been drastically reduced, which provides lower carbon air emissions [44]. Lockdowns and decreased mobility of vehicles and people improved the air quality and surrounding environment. In the paper presented by Ref. [45] the daily global emissions of $CO_2$ decreased for 17% in April 2020 compared with the mean values in 2019, while the overall impact on annual emissions in 2020 depends on the duration of the lockdowns. The correlation between COVID-19 lockdown and the air quality improvement from 44 regions in northern China was analysed in Ref. [46]. The air pollution mitigation in their examinations were associated with the travel restrictions. In the research presented in Ref. [47] the CO concentration in Sao Paulo, Brazil decreased by 64,8% compared with the average of the past 5 years due to the partial lockdown.

Mehmood [48] and Cole [49] reported positive relationship between long term exposure on PM2.5 concentrations and COVID-19 daily cases, related to hospital admission and deaths in India, Pakistan and Iraq. The results taken from 15 provinces in Iran from April to June 2020 showed that dry land provinces had lower rates of cases, while air temperature was positively correlated with the number of cases. Air temperature, dry lands, and population were important factors in controlling the spread of coronavirus [50]. Alike, strong correlation was associated between PM2.5 and PM10 concentrations and COVID-19 case fatality rates (CFR) in 49 Chinese cities, including Wuhan, the epicentre of the COVID virus [51]. In the study presented by Yao [52], the authors showed that for every 10 $\mu g/m^3$ increase in PM2.5 and PM10 concentrations, COVID-19 CFR also increased by 0.24% and 0.26%, respectively. Similarly, [40] at the Harvard University T.H. Chan School of Public Health showed that an increase of just 1 $\mu g/m^3$ of PM2.5 concentration is associated with 15% increase in COVID-19 deaths. Another research that concludes the positive correlation between the COVID-19 mortality and high exposure of PM concentrations are presented in Refs. [48,53]. They analysed that persons living in an areas with high levels of PM2.5 concentrations are more sensitive to developing respiratory and cardiovascular diseases.

According to National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA) the levels of Carbon Dioxide ($CO_2$) and other air pollutants decreased in Wuhan, China during the lockdown days [54,55]. They also reported that in some of the COVID-19 epicentres, such as Wuhan, Italy, Spain, USA etc, air pollution reduced up to 30% [43]. In the reports presented by ESA, the level of $NO_2$ concentrations decreased by 30–54% in Paris, Milan and Rome ([4,56].

For years the city of Skopje has been facing the problem of bad air quality, especially during the winter months. The enormous concentrations of PM have been detected for a number of years in the capital city of North Macedonia [57]. North Macedonia has been strongly affected by COVID-19, with significant death rate associated with the virus. However, more data and analyses are required to investigate if that could be also attributed to high PM concentrations in the air.

The aim of this paper is to analyse the influence of the COVID-19 restriction rules and lockdowns on air quality reduction, as well as the particular influences of the meteorological factors, derived by sensor measurements, such as wind speed and direction, relative humidity, and temperature on air quality and their impact on PM mitigation.

## 3. Methods

The following two subsections provide detailed descriptions of the location of the measurement, test equipment and the measurement system used for data acquisition. The statistical tools which are used to analyse the collected data are given in Subsection 3.3.

### 3.1. Sensor test facility

In order to identify the influence of the green areas, traffic and movement of people, different positions of the sensor nodes were chosen. In 2018 the positions of the nodes were located near the Faculty of Electrical Engineering and Information Technologies building, as depicted in Fig. 1 (the sensor nodes are depicted in magenta). At the beginning of the measurement setup, the green wall structure was installed. The green wall structure consisted of two rows of hedera helix plants, which were planted during the spring period. The sensor nodes were placed on a platform, where two photovoltaic panels were already installed. The sensor node 3′ had a relative position closer to the secluded green area, while the sensor node numbered 2′ was located closest to the green wall structure. Sensor node 1’ had a position close to a road, where vehicles and people are usually crossing. The measurement results considering the impact of the green wall structure on air quality improvement is already presented in Refs. [28,29].

Later in 2019, the positions of the nodes were changed. As depicted in Fig. 1 (the sensor nodes are depicted in magenta) the sensor node 1 is close to the pedestrian pavement, sensor node 2 is located near the green area. Near the location of the sensor node 2 there is a small green area (as a part of the building patio).

This paper analyses the period before COVID-19 lockdown restriction rules (with emphasis on the summer months, 2018), during the COVID-19 lockdown (2020), and the summer months in 2022, when life gets back to normal. Due to technical problems with insufficient data in 2019 and 2021, the measurement results are not presented in this paper.

### 3.2. Measurement system description

The originally developed measurement system based on wireless sensor network technology is composed of PM and gas sensors for monitoring the parameters of the air quality. The measurement monitoring system consists of few sensor nodes each of them containing four sensors and a Wi-Fi module integrated on a single-board controller. Sensors integrated in each node can measure the following parametersPM2.5, PM10, CO and $NO_2$. SDS011 is the integrated device including the PM2.5 and PM10 concentrations measurement. This sensor unit can measure the particle concentration between 0.3 μm and 10 μm. MiCS-4514 is the other sensing unit that has integrated two sensors for CO and $NO_2$ measurements. The main characteristics of the sensing units are presented in Table 1.

The controller is responsible for processing the data, before they are transmitted to the network. This type of integrated controller can be used for various applications, from low-power sensor networks to high demanding power applications like music streaming and voice encoding. The main characteristics of the controller are presented in Table 2.

The Wi-Fi modules that are integrated part of the sensor nodes, send data to the closest routers, which are located in the Faculty building. The collected data from the closest routers are uploaded on an open platform [58] and can be monitored on-line or downloaded for additional analyses. The hardware details and the main characteristics of the described setup are available in Ref. [59].

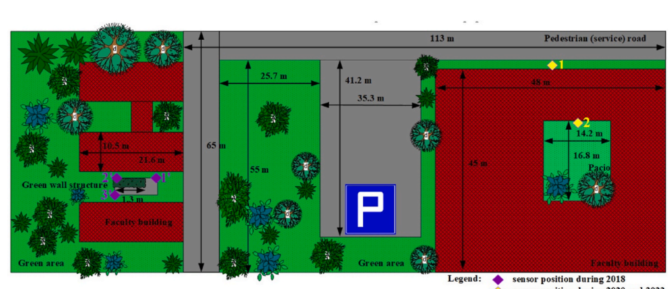


Fig. 1. Overview of the location with the disposition of the sensor nodes during 2018, 2020 and 2022.

**Table 1**
Main characteristics of the sensing units.

| | SDS011 | MiCS-4514 |
|---|---|---|
| Measurement parameters | *PM2.5, PM10* | *CO, $NO_2$* |
| Supply voltage | 5V | 4.9V–5.1V |
| Operating temperature range | −20°C-50 °C | −30 °C -85 °C |
| Range | 0.0–999.9 μg/m$^3$ | / |
| CO detection range | / | 1–1000 ppm |
| Sensing resistance in air | / | 100–1500 kΩ |
| Maximum working current | 220 mA | |

**Table 2**
Main characteristics of the controller.

| | Controller |
|---|---|
| Measurement parameters | *EPS32* |
| Supply voltage | 2.7V–3.6V |
| Operating temperature range | −40 °C -85 °C |
| Module interface | SD Card, UART, SPI, I2C, Motor PWM |
| Wi-Fi frequency range | 2.4GHz–2.5 GHz |

### 3.3. Statistical tools

For the analysis of the sensor measurement data, a set of statistical tools: descriptive statistics, cross-correlation, hypothesis tests were used. To determine the maximum, minimum, mean and variance for the observed periods, descriptive statistics were used, while hypothesis tests are necessary for determining distribution, regularity and statistically significant difference between measurements. The cross-correlation measures the similarity of two random values, but does not give a functional dependence between them. The functional dependence between the independent and the dependent variables are possible by implementation of a regression model. The variation coefficient is the ratio of the standard deviation to the mean and it measures the dispersion around the mean. Higher values of the coefficient lead to higher values of variability.

The aim of this paper is to determine the influence of the sensor node location and other conditions on PM concentrations mitigation. In order to investigate the influence, hypothesis tests were performed. To perform these tests, $H_0$, and the significance level α should be defined. The null hypothesis is also known as status quo.

**H0**. There is no difference between conditions. (1)

The value of α was set to 0.05, that indicates a 5% risk of concluding that a difference exists, when there is no actual difference. In each test p-value is determined for the given data and the obtained p-value is compared to the significance level α. The Null hypothesis $H_0$ is rejected when p-value $\leq \alpha$, which means that differences between the considered conditions are statistically significant, while if p-value $\geq \alpha$, then the Null Hypothesis can be confirmed, which means that there is no statistically significant difference between the conditions.

Additionally, to determine if there is a statistically significant difference between conditions when the variables do not have normal distribution, non-parametric tests are performed. For this analysis, non-parametric version of ANOVA known as Friedman test was applied [60].

## 4. Results and discussion

The air quality measurement system started with the acquisition of the sensor measurement data in May 2018 at the Faculty of Electrical Engineering and IT in Skopje.

This paper presents measurement periods taken through the summer months concentrating on the period 15th June-14th October during 2018, 2020 and 2022. The period was chosen because of the COVID-19 pandemic declared by the World Health Organization (WHO) [61], which led to introduction of restriction rules and quarantines. The measurement set for the period December 2018–February 2019 when the air pollution is usually higher compared to summer months was already presented in Refs. [28,29]. The highest PM concentrations, which reach the values of 306 μg/m$^3$ for PM2.5 and 391 μg/m$^3$ for PM10 and occurred around midnight on 19$^{th}$ of January 2019, have been measured. These values are far above the allowed annual average PM concentrations for PM2.5 and PM10.

### 4.1. Experimental measurements

As described above, the measurement period encompasses summer months in the years before, during and after COVID-19 restrictive measures. During the pandemic, the Faculty building was mostly empty and the faculty staff were mainly working from home, the exams and the lessons were held online. At that period the traffic in the campus was drastically reduced compared to the years before.

The graphs on Figs. 2 and 3 present hourly average data for PM2.5 and PM10 concentrations respectively, including the first analysed period of about 7 days, starting from June 15, 2018 until 21$^{st}$ of June 2018, and serve to show typical summer days, with periods of low PM concentrations. The analysed periods show higher average values of PM concentrations during the day, then during night-time.

The graphs on Figs. 4 and 5 present hourly average sensor data for PM2.5 and PM10 concentrations respectively, for the second analysed measurement period of about one week, starting from 24$^{th}$ of June 2020 until 30$^{th}$ of June 2020. Even more, this is the period when the first anti-COVID restriction rules (quarantine) started. The values for PM2.5 and PM10 concentrations are in the range of the allowed annual average PM concentrations.

Also, it can be noticed that the concentration of PM2.5 is higher at the location of Node 2 (than at Node 1) but lower for PM10 (it is important to note that this sensor is located in the building patio).

The third analysed period is chosen to be from 20$^{th}$ of June 2022 until 26$^{th}$ of June 2022. Figs. 6 and 7 present hourly average sensor data for PM2.5 and PM10 concentrations, respectively.

The results presented in Figs. 2, Figure 3, Figure 4, Figs. 5, Figs. 6 and 7 suggest that there is a difference between the concentration of PM concentration (PM2.5 and PM10) in these different locations (during the whole period, daytime and night-time). These results indicate that during night-time the level of PM concentration is lower compared to the PM concentration during daytime, which was not case during the winter months. The highest values for PM concentration for winter months were reached during night-time.

### 4.2. Statistical analysis of the measured sensor data

This paper analyses the sensor data collected during no heating period in 2018, 2020 and 2022. Due to the COVID-19 restrictions in spring and summer 2020, the observed period for all three years is

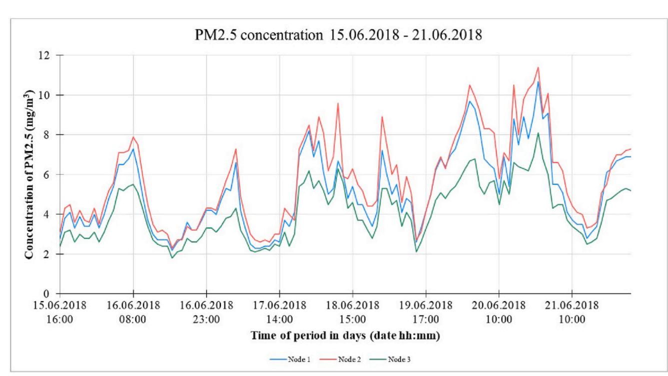


**Fig. 2.** Concentration of PM2.5 for one-week, average hourly sensor data.

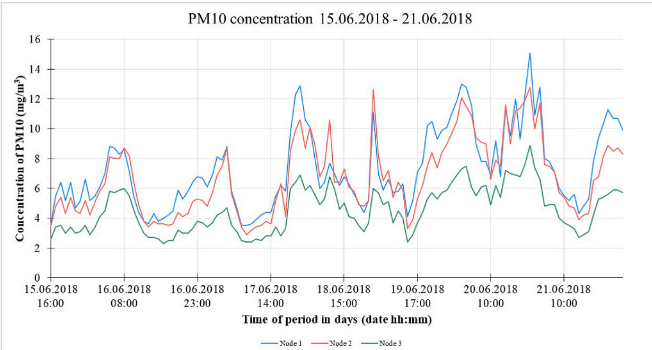


**Fig. 3.** Concentration of PM10 for one-week, average hourly sensor data.

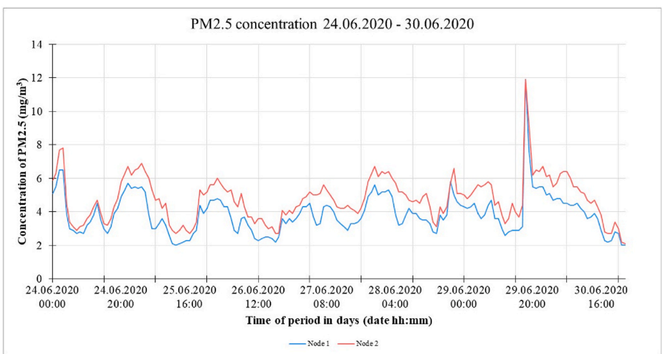


**Fig. 4.** Concentration of PM2.5 for one-week, average hourly sensor data.

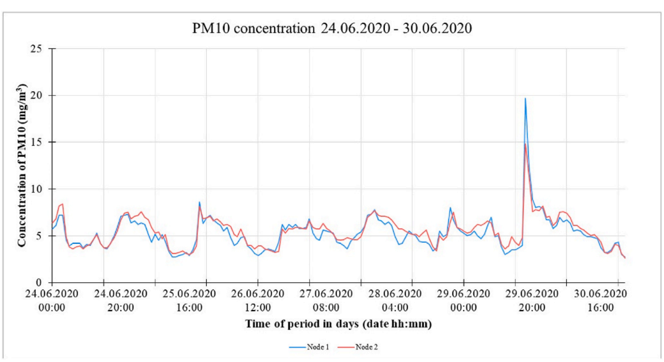


**Fig. 5.** Concentration of PM10 for one-week, average hourly sensor data.

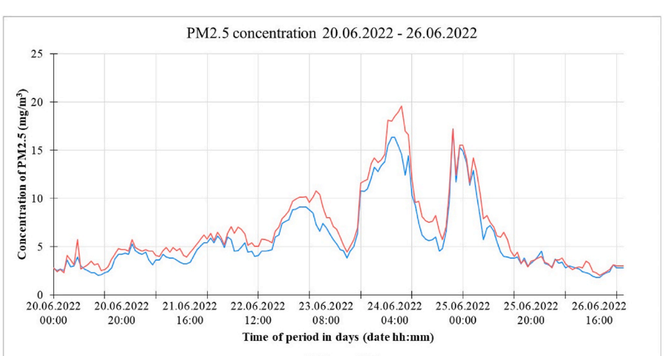


**Fig. 6.** Concentration of PM2.5 for one-week, average hourly sensor data.

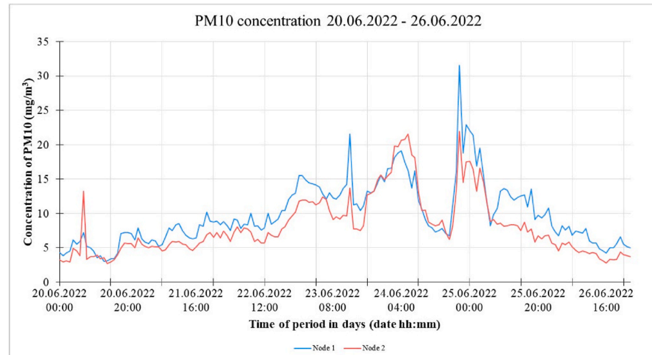


**Fig. 7.** Concentration of PM10 for one-week, average hourly sensor data.

reduced to 15th June - 14th October. In 2018 the collected data from three sensor nodes were analysed, while in 2020 and 2022 the measurement data from only two sensor nodes were calculated. The positions of the nodes are already given in Fig. 1. The presented results are obtained by statistical analysis of the average value the PM2.5 and PM10 concentrations that active sensor nodes registered at the same moment of time.

Overview of the meteorological dataduring the observed periods is given in Table 3, and the results indicate that the weather conditions in the observed three years are similar. In each year more than 55% of the time the wind in Skopje has been in direction west, north-west and north.

The descriptive statistics of the PM2.5 and PM 10 are presented in Table 4. It actually presents the calculated descriptive statistics for: i) the whole measurement period, ii) daytime (8 a.m.–8 p.m.), and iii) night-time (8 p.m.–8 a.m.). Previous results [28,29] suggest that the night-time period, i.e. the period from 8 p.m. to 8 a.m. is related to peaks in the concentration of PM, although during this period the activity in the faculty zone, movements from both people and vehicles in the near vicinity of the experimental set up are set to minimum. Following the indication of previous work, the analyses in this paper were also done for both daytime and night time. The observed peaks in the night-time period are not directly caused by the activity at the Faculty zone, but are related to other sources of pollution. Investigation of the pollution sources is not in the scope of this paper.

The Pearson correlation coefficient shows statistically significant positive correlation between the PM concentration and humidity (0.17 and 0.11 for PM2.5 and PM10, respectively) and visibility (0.08 and 0.09 for PM2.5 and PM10, respectively). Statistically significant negative correlation between PM concentration and cloud cover (−0.04 and −0.05 for PM2.5 and PM10, respectively), precipitation (−0.06 and −0.08 for PM2.5 and PM10, respectively), temperature (−0.04 for PM2.5 and PM10) and wind speed (−0.15 and −0.17 for PM2.5 and PM10, respectively) is observed.

Kolmogorov-Smirnov and Sahapiro-Wilk tests [62] are

**Table 3**
Descriptive statistics for the meteorological parameters for the period 15th June-14th October by year.

| | 2018 | | 2020 | | 2022 | |
|---|---|---|---|---|---|---|
| | range | mean | range | mean | range | mean |
| Temperature (°C) | [9,35] | 22.3 | [9,36] | 21.91 | [7,40] | 22.17 |
| Real feel temperature (°C) | [7, 33] | 22.2 | [8, 35] | 22.27 | [7,40] | 22.16 |
| Cloud cover (%) | [0, 99] | 97.00 | [0, 92] | 26.74 | [0, 100] | 23.96 |
| Humidity (%) | [18, 92] | 54.03 | [16, 92] | 55.79 | [9, 95] | 50.98 |
| Precipitation (mm) | [0, 1.2] | 0.02 | [0, 2.4] | 0.06 | [0, 2] | 0.03 |
| Wind speed (km/h) | [0, 21] | 8.65 | [0, 23] | 5.83 | [0, 26] | 6.48 |

**Table 4**
Descriptive statistics for the period 15th June – 14th October by year, for: i) the whole measurement period, ii) daytime (8 a.m.–8 p.m.), and iii) night-time (8 p.m.–8 a.m.).

| | | PM2.5 | | | PM10 | | |
|---|---|---|---|---|---|---|---|
| | | 2018 | 2020 | 2022 | 2018 | 2020 | 2022 |
| Mean | i) | 5.04 | 4.35 | 4.45 | 6.33 | 6.06 | 6.37 |
| | ii) | 4.04 | 3.89 | 3.97 | 5.54 | 4.91 | 5.79 |
| | iii) | 5.73 | 5.42 | 4.93 | 7.19 | 6.81 | 6.95 |
| Maximum | i) | 15.27 | 84.60 | 23.00 | 18.53 | 134.80 | 47.70 |
| | ii) | 14.27 | 13.56 | 15.50 | 17.23 | 26.35 | 29.95 |
| | iii) | 15.27 | 84.60 | 23.00 | 18.53 | 134.80 | 47.70 |

nonparametric tests used to assess the normality of a given data set. The Kolmogorov-Smirnov test compares the cumulative distribution of the data set with a theoretical normal distribution, while the Sahapiro-Wilk test compares the sample mean and variance with theoretical values. Both tests can be used to identify departures from normality and, in some cases, can be used to determine whether the data should be transformed or whether a nonparametric test should be used instead of a parametric test. The tests Kolmogorov-Smirnov and Sahapiro-Wilik confirm that the analysed sensor data does not have normal distribution. At the same time the observed data results with positive kurtosiss and positive skewness. A positive kurtosis indicates that a distribution has a higher peak and longer tails than a normal distribution. This means that there are more extreme values in the distribution. A positive skewness indicates that a distribution has a long tail on the positive side of the mean (the right side of the distribution), and the mode is less than the mean.

### 4.3. Hypothesis tests

The obtained results, presented in Table 4, indicate the following statements.

a) The concentration of PM is higher during night-time compared to daytime for all years considered; and
b) The concentration of PM in 2020 is smallest compared to 2018 and 2022.

Therefore two null hypothesis are defined:

$H_{a0}$: There is no difference between the concentration of PM2.5 (resp. PM10) during daytime and night-time; $H_{b0}$: There is no difference in the concentration of PM2.5 (resp. PM10) in the years 2018, 2020, and 2022.

As the considered sensor data does not have normal distribution, a non-parametric hypothesis test should be performed. The variables are independent, hence Mann-Whitney $U$ test and Kruskal-Wallis test should be performed for hypothesis $H_{a0}$ and $H_{b0}$, respectively.

The Mann-Whitney $U$ test for the hypothesis $H_{a0}$ rejects all six null hypothesis, and confirms that there is a difference in the concentration of PM2.5 and PM10 during daytime and night-time for all three years, i.e. that the concentration of PM is smaller during daytime. The Mann-Withney $U$ test results with corresponding $z$ values, given in Table 5, that can be converted into an effect size estimate $r$ by the Rosenthal's formula [63] $r = \frac{Z}{\sqrt{N}}$. The results show that the effect of daytime/night-time is medium for 2018 ($r > 0.3$) , while for 2020 and 2022 the effect is small ($r \leq 0.3$).

The Kruskal-Wallis test [64] rejects the null hypothesis $H_{b0}$ for PM2.5 and PM10 with p-value approximately 0.000, so it confirms that there is a difference in the concentration of PM. The post hoc test for PM2.5 shows that there is statistically significant difference between 2018 and 2020, as well as between 2018 and 2022, but the difference is not significant when 2020 and 2022 are compared. The same post hoc test for PM10 locates a statistically significant difference between all pairs, i.e. 2018-2020, 2018-2022, and 2020-2022. The Kruskal-Wallis test is a non-parametric statistical test used to compare the medians of three or more independent samples. In this case, the Kruskal-Wallis test has been used to compare the concentration (or median) of a given set of data across different years. The test has confirmed that the highest concentration was in 2018, and the smallest concentration was in 2020. To evaluate the effect size, a pairwise Mann-Whitney test [65] is performed, and the results are presented in Table 6. The Rosenthal formula is a statistical measure that can be used to evaluate the magnitude of an effect size. When applied, it can show whether the effect size is small, medium, or large. In this case, the application of the Rosenthal formula has revealed that the effect size is small. This means that the effect size is not very pronounced, and any observed changes in the data are likely to be minimal.

## 5. Conclusions

In this contribution the analyses of the collected data from an air quality sensor measurement system for PM monitoring is presented. The used WSNs system enables collection and monitoring of air quality related data. The collected data can be further processed in order to evaluate the influence of green areas on PM concentration. In this paper, specific statistical tools are used to perform the required analyses.

The measurement results collected from the sensor system for a period of three years indicate that particular matter concentrations tend to be lower in the area near to the green zones. Therefore, it can be concluded that the position of the sensor nodes plays an important role when the PM concentration is concerned. The measured values of PM10 concentration are lower at Node 2 (which is located in the building patio), while the average PM2.5 concentration for the analysed period is slightly lower at Node 1 (compared to Node 2) during the summer months 2020 and 2022. For the first analysed period, summer months in 2018, the PM2.5 and PM10 concentration are lowest at sensor node 3′, which is located close to the green area, while the PM2.5 and PM10 concentrations are highest at sensor node 1', which is positioned close to the parking place.

During the Covid-19 pandemic higher pollution during the night hours was not detected. Even more, the PM concentration was significantly lower during night time. The strongest correlation between PM2.5 and PM10 concentration and the wind speed is confirmed. Also, the negative correlation between the PM concentration and wind speed for all three locations is verified. Similarly, insignificant correlation between PM concentrations and the actual temperature, and slightly stronger correlation between the PM concentrations and the real feel temperature is reported. Insignificant correlation is noticed between PM concentrations and the pressure, and between PM concentrations and the humidity.

From this research, it can be concluded that few factors have significant influence in the reduction of PM concentration during the analysed period. During the COVID-19 lockdown period lowest values of

**Table 5**
Results from Mann-Whitney $U$ test for hypothesis $H_{a0}$.

| | Z value for PM2.5 | Z value for PM10 | Number of observations N |
|---|---|---|---|
| 2018 | −13.343 | −14.189 | 1581 |
| 2020 | −8.767 | −8.740 | 2299 |
| 2022 | −8.353 | −7.934 | 2258 |

**Table 6**
Results from pairwise Mann-Whitney $U$ test for hypothesis $H_{b0}$.

| | Z value for PM2.5 | Z value for PM10 | Number of observations N |
|---|---|---|---|
| 2018–2020 | −12.06 | −7.398 | 3880 |
| 2018–2022 | −10.542 | −3.030 | 3837 |
| 2020–2022 | No difference | −4.601 | 4555 |

PM concentrations are measured, while in 2018, before the pandemic, the highest values of PM concentrations are observed. The green areas at the Faculty patio, the reduced traffic of vehicles and the reduced mobility of the faculty staff, have high impact in the reduction of PM concentration.

## Declaration of competing interest

None.

## Data availability

Data will be made available on request.

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