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The effect of small green walls on reduction of particulate matter concentration in open areas

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ABSTRACT

A major concern in urban areas is the low quality of air, with high levels of particulate matter (PM), consisting of black carbons, volatile organic compounds and various pollutants that are hazardous for the human health and the global environment. Thus, there is an urgent need to decrease air pollution by implementing various short and long-term measures. One of the methods for decreasing air pollution in urban areas is increasing the green infrastructure as plants absorb the particulate matter through their leaves and stems. The initial step in dealing with this problem is raising the public awareness, which is generally low in Skopje and the Balkan region.

The aim of the research is to quantify the positive effects on green infrastructure on air pollution and provide research-based inputs that can be used by local governments and decision makers. This paper presents data from continuous measurements on a location in Skopje, provides an assessment of the influence of green zones on air quality in urban areas and correlates it with meteorological factors. This is achieved by using an innovative, low-cost, easy replicable and energy-efficient system, consisted of green wall and stations for monitoring the air quality which are based on wireless sensor network technology.

By using statistical tools as Freidman and Mann-Whitney tests, the impact of the relative position of the measurement sensors and the green areas and other objects to the PM concentrations is quantified. The performed analyses confirm that green areas, including green walls, have a high impact in the reduction of PM concentrations in their proximity.

The differences in measured values obtained by measurement nodes positioned in relatively small distances are not negligible, thus implying that the relative position of the measurement nodes to the green infrastructure influences the measured PM concentrations. Therefore, the measurement location should be carefully considered for any air quality monitoring system. Measurements with higher spatial granularity should be used for modelling and air quality forecasting purposes.

The results in this paper show that the green area mitigates the PM of 2.5 or less micrometers (PM2.5) on average by 25% and PM of 10 or less micrometers (PM10) on average by 37% compared to the neighboring non-green areas. The results show a strong correlation between PM2.5 and PM10. In Skopje, the combination of low temperatures, high humidity and no, or low wind speed lead to high PM concentrations.

The presented algorithm compares the statistically obtained data to the reference categories from WHO (from very low to very high, with reference to PM2.5). The described methodology is used to develop a simple decision-making support algorithm for local governments to support their decisions on applying PM mitigation measures.

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1. Introduction

Air pollution is among the highest environmental risks for human health. It is a complex mixture of dangerous substances including gases as ground–level ozone, carbon, nitrogen and sulphur oxides and hydrogen sulphide, particulates and biological compounds. PM consists of nitrates, sulphides, black carbons and organic matter and is among the pollutants with high negative impact on human health (Heal et al., 2012). PM10 is usually emitted from different heating sources and power plants, while PM2.5 is related to exhaust gases from vehicles, burning wood, plastic and waste.

The necessity to overcome air quality problems has led to development of numerous solutions, including implementation of various types of green infrastructure, as green walls and green roofs. Green walls are vegetated vertical surfaces where plants are attached to the surface by various techniques, providing good conditions for growing dense and diverse vegetation (Bolton et al., 2014). The plants act like filters for nitrogen dioxide and fine dust from the air. Green roofs are vegetated roof systems with waterproof membranes and additional systems for irrigation and drainage. The benefits of the green walls and roofs are presented in the state-of-the-art systems review in (Radić et al., 2019), where thermal performance, reduction of air pollution and noise, hydrological, social, visual, educational, and economic benefits and installation costs are discussed. Furthermore, according (Saadatian et al., 2013), green roofs reduce building temperature up to 20 °C, absorb about 60% of solar radiation and reduce energy for air conditioning between 25% and 80%. Green walls could decrease temperature by 6.1 °C on sunny days and by 4 °C on cloudy days, as discussed in (Cuce et al., 2016). According to the research in (Coma et al., 2017), the energy savings achieved by implementation of green walls estimate to 58.9% and of double-skin green facades to 33.8% compared to a reference system. The review presented in (Radić et al., 2019) shows that the costs of living walls in Europe are roughly between 400 EUR/m^2 to 1200 EUR/m^2, the estimate being valid for different structures (framed boxes, carrier system, cable wire and geotextile), while green facades are associated with lower costs, which for Turkey and Europe vary between 35 EUR/m^2 and 75 EUR/m^2.

There are a number of studies focusing on quantification of the positive effects of green infrastructure on air pollution mitigation. The dispersive effect of trees decreases PM2.5 concentration by 9%, as presented in the study about Leicester (Jeanjean et al., 2016). The authors in (Foster et al., 2011) estimate that carbon dioxide emissions can be reduced between 1.7% and 2.8% by green fences consisted of grass and trees. Green areas (lawns with and without trees) contribute to reduction of air pollution, especially PM. As shown in (Zheming et al., 2015), transect across a lawn with trees has fewer spikes in PM2.5 concentrations than a transect crossing a treeless lawn. As presented in (Radić et al., 2019), green wall facades and living walls show reduction of concentrations of nitrogen dioxide and PM10 up to 15% and 23% respectively, for cases related to urban canyons. The reduction of peak PM2.5 concentrations by green facades and living walls are observed to be 45.3% and 74.1% respectively, considering that these reductions are related to specific vegetation, which is a topic discussed in detail in (Viecco et al., 2018).

The effects on air pollution mitigation are bound to the specifics of the location and climate. The study (Setälä et al., 2013) performed for northern climates reports decrease in PM concentration in areas with trees, compared to areas without trees, for both summer and winter months, with the remark that the difference is not so significant. Meteorological factors as humidity, wind speed, wind direction and temperature influence air quality, but there are no common quantitative rules to determine the dependences (Latini et al., 2002). The authors in (Gaffin et al., 2010) observed that humidity has the highest impact on PM10 removal, followed by wind speed and by temperature. A different observation is made in (Xu et al., 2018), concluding that for specific locations, humidity, combined with low wind speed has an adverse effect on PM 2.5. Rough terrain contributes to deflection of pollutant gases and particles and changes the influence of wind speed and direction, as shown in (Hewson et al., 2012). Analyses of historical data from 15 years for a given location show that the increase of wind speed has a positive effect on PM10 mitigation and short-term analyses showed that stagnant, high pressure conditions increase PM10 concentration (Seo et al., 2018). The dominance of wind speed and wind direction on the concentrations of contaminants along with mixing of the layer heights is discussed in (Schäfer et al., 2014).

Providing measurements is the initial step for evaluating the effects of implemented measures against air pollution. The developments of integrated on-chip technologies have provided conditions to change the traditional approach in measurement of pollutants. A new generation of sensor systems with relatively small dimensions and mobility characteristics has emerged as a possible solution (Latini et al., 2002). Typically, these systems are developed as wireless sensor networks (WSNs), with nodes comprising of a battery powered unit, sensors, a microprocessor and a transceiver and are widely used in various types of applications, as presented in the survey in (Rashid and Rehmani, 2016). Some WSNs require autonomous and independent operation as they are implemented in remote locations with underdeveloped infrastructures (Srbinovska et al., 2015). A drawback of sensor nodes is the energy consumption, which should be as low as possible. This can be achieved by implementation of energy constrained dominant set algorithms as proposed in (Albath et al., 2013), by adequate routing algorithm, as proposed in (Manso et al., 2015) which also contributes to extension of WSNs lifetime, or by optimization of WSNs coverage, as it influences sensors' consumption and the network lifetime (Wang et al., 2014). Providing supply for the sensor nodes bateries by renewable energy sources is additional approach in dealing with this issue, as discussed in (Srbinovska et al., 2016). Assimilation of the WSN technologies with Cognitive Internet of Things would increase their effectiveness and lower their costs, as debated in (Graessley et al., 2019). Introducing artificial intelligence in WSNs applications may increase the cumulative revenues, especially by improving predictive maintenance of remote infrastructures where WSNs are often applied (Udell et al., 2019). The authors in (Milward et al., 2019) made estimates and performed analysis related to implementation of artificial intelligence, the benefits of using industrial big data analytics for organizations and the progress achieved by implementation of the most popular industry 4.0 applications. The modelling equations and probability sampling methodologies which are used to analyse the bid data algorithmic decision making processes are presented in the work by (Kovacova et al., 2019).

This paper shows the results from PM concentrations measurements obtained with an air quality monitoring system which uses WSNs for data acquisition (Srbinovska et al., 2017). It is a low cost, efficient and easily replicable system, as confirmed in the analyses of the costs associated with its implementation, replication and the consumption of the WSN equipment. The measured data and additional statistical analyses presented in this paper confirm and quantify the effects of the green wall and existing green infrastructure (green zones with threes) in the near proximity of the measurement system. Among the objectives of the work was to systematically apply adequate statistical tools and test the impact of the green infrastructure on each measurement location. Our analyses show that the hypothesis test together with corresponding post-hoc tests should be applied along with other statistical tools to properly evaluate the effects of green infrastructure on PM reduction, which has not been done in related work. The presented methodology is an alternative approach in analyses of measured data and is used to clearly describe the effectiveness of the relative location of the green infrastructure on mitigation of both PM10 and PM2.5. The results presented in this paper show that descriptive statistics performed on day and nighttime occurrence and under normal and extreme conditions support the significance of the location of the green infrastructure on PM mitigation. Furthermore, correlation between wind speed, humidity, temperature and PM concentrations is established for the measurement location. While the results are obtained for a specific location, the conclusions are valid for locations with mid-continental climate conditions. The paper also shows a decision-supportive algorithm that is developed based on the performed measurements and analyses. As discussed in (Bowen and Lynch, 2017), the overall benefits of green infrastructures are often neglected due to the local government's inability to acknowledge these benefits. By providing relevant data and easy-to-implement tools for the local governments, these barriers may be removed. The applied system and methodology may serve as a basis for developing "environmentally conscious" systems which use advanced technology to analyse air quality and based on the results, implement green infrastructures for its improvement.

2. Methods

The following two subsections provide detailed descriptions of the location of the measurement, equipment and the WSN monitoring system used for data acquisition. The statistical tools which are used to analyse the collected data are given in Subsection 2.3.

2.1. Test facility

The experiment was set up on a location near the Faculty of Electrical Engineering and Information Technologies in Skopje. Near the location, there is a small green area consisted of deciduous trees, bushes and evergreens, one storey small buildings and a parking lot. The location was chosen to capture the effects of green areas as well as the influence of movement of vehicles and people. As depicted in Fig. 1, the sensor node 1 is nearest to the road and pedestrian pavement, the sensor node 2 is located near the green wall structure and the node 3 is located opposite of the node 2, but nearer to the green area.

The green wall structure consists of two rows of hedera helix plants, which were planted during the spring period. The wall was not very mature and dense during the measurement campaign presented in this paper, with lower density and greenery in the winter months. It is worth to note that the hedera plants are considered among the plants with relatively high PM dry deposition (Viecco et al., 2018), i.e. has a higher PM mitigation impact. The nodes are placed on a platform, where two PV panels are placed. The node 3 has a relative position closer to the secluded green area and is not directly shielded by an adjacent object, thus the PM is easier to be swept by wind or rain. The node 2 is relatively close to the PV installation which may reduce the influence of meteorological factors in dust reduction to some extent. This node is also relatively further away from the green area compared to node 3, but it is near green wall structure.

2.2. Description of the system

The WSN monitoring system consists of these three nodes, each of them containing four sensors and a Wi-Fi module integrated on a single-board controller. The sensors measure concentrations of PM2.5, PM10, carbon monoxide (CO) and nitrogen dioxide (NO_2). For measurement of the PM particles in the air the system uses a direct technique, which provides continuous measurement (sampling interval is in seconds or minutes). The sensors can measure PM in the range of 0.3–10 μm. The concentrations of CO and NO_2 are measured with a combined sensor based on resistance sensing. The OX (oxygen) sensor resistance in the presence of NO_2 is increasing, while the RED (reduced) sensor resistance in the presence of CO and hydrocarbons is decreasing. The controller processes the acquired data before transmitting them 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 Wi-Fi modules of the nodes send data to a router that is located in one of the buildings depicted in Fig. 1. From that router, the collected data is uploaded on an open platform (Internet of Things open platform, 2020) and can be monitored on-line or downloaded for additional analyses. The system is designed to have low power consumption and overall low costs. The details of the hardware used for the described setup are available in (Velkovski et al., 2019).

2.2.1. Costs

The system was constructed from used materials (old wooden boards from discarded furniture for the shelves and used plastic bottles for plant pots) as well as new materials for constructing the rails for the plant pots. The costs for the plants and the rails were about 135 EUR. The costs for the monitoring system consist of the costs of the sensors, the costs for the power supply system and additional cable wiring. The total costs for the sensors were about 145 EUR and the other costs amounted to 65 EUR. There were no additional costs for the router and data transmission, as faculty equipment and network were used. The overall costs for the practical implementation of the system amounted to 180 EUR/m^2, therefore the system can be considered as a low-cost system compared to the systems described in the review in (Radić et al., 2019). The costs would amount up to 250 EUR/m^2 if the system is designed with additional rails to provide higher plant density. The costs for the measurement equipment are about 60% of the total costs, so green walls built from used materials and without the described monitoring system would cost approximately 100 EUR/m^2. New materials would certainly increase the costs, but even in that case, the system would be on the lower cost end compared to the available data. At this stage, the system is implemented without automatic irrigation system.

The operation and maintenance costs of this system are related to removing dried and planting new vegetation, trimming, additives for plant nutrition, replacement sensors. For the described system, these costs may vary from 20 EUR to 100 EUR annually, the latter including replacement of a sensor and about half of the vegetation. The operational costs of the system also include the costs for electricity consumption of the sensors and the router. Considering that the retail electricity prices vary around the world, these costs will depend on the country of application. For example, Denmark has the highest household electricity price in Europe which is 0.2924 EUR/kWh. The price in Denmark is almost five times higher than the average price in Kosovo, which is 0.0605 EUR/kWh and is the lowest price in Europe. Consequently, the annual electricity costs would differ accordingly.

Costs of sensors that can be used in WSN application as well as traditional PM monitoring stations are presented in Table 1. It is obvious that WSN application belong to the low-cost end of the PM monitoring systems. The approach in designing low cost WSNs is based on open source cloud applications for data collection, sensors with low consumption and low prices, and optimization of

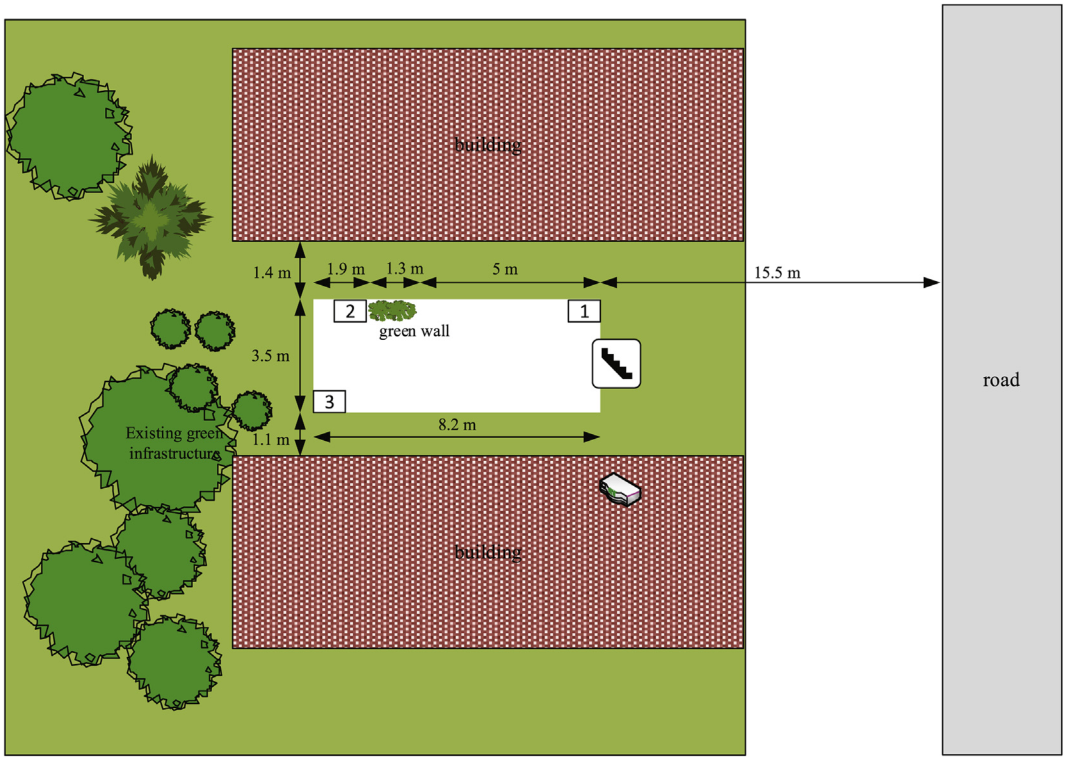

Fig. 1. Overview of the location with the disposition of the sensor nodes.

topology and routing. WSN with similar design approach is discussed in (Lazarescu, 2014), showing that using open, cloud-based data access is preferable to balance latency and energy consumption of the low power communication segments. As discussed above, the system presented in this paper uses open source cloud platform for data collection and low-cost sensors using available AC power supply. This technology is significantly cheaper than traditional PM monitoring stations, as described in Table 1.

The system is easy to install and replicate using the current sensor node configuration and the green wall construction. Table 2 presents approximate costs of the system if it is replicated on a different location with large coverage area, using the same sensor node configuration and the same green wall construction. The calculations are done assuming a circular sensing area equivalent to 1000 m^2, sensors with 80 m transmission range and the wireless router placed in the centre of the area. The costs for implementation of several 2 m^2 green wall constructions sufficient for this coverage area, would not exceed 2000 EUR.

Table 3 presents average power consumption and total costs of the sensor monitoring system per day. The calculations take into account the approximate costs of the system per day and the cost of the system with more than 3 sensor nodes. The wireless router uses the IEEE 802.11n standard based on multiple antennas to increase data rates. The purpose of this standard is to improve data rates with a significant increase in the maximum net data rate from 54 Mbit/s to 72 Mbit/s. According to this standard the maximum number of nodes connected to the wireless router should not exceed 200 units. In order to eliminate the worst scenario using 200 sensor nodes on the same router, the calculations are made assuming maximum 150 sensor nodes on the same router.

Table 1
Specification of different low-cost PM sensors compared to traditional PM monitoring stations.

PM sensors Model	Size (mm)	Power supply	Maximum current consumption (mA)	Cost (EUR)	Particle diameter size (μm)	Concentration range of measurement
Novafitness SDS011	71 × 70 × 23	5 V DC	80	18.5	<0.3	0.0–999.9 μg/m^3
Alphasense OPC-N2	75 × 64 × 60	5 V DC	175	8.8	0.38–17	0,1–1500 μg/m^3
Dylos DC 1700	178 × 114 × 76	110 V AC or battery	NA	377	0.5–2.5	0-106 particles/cm^3
Plantower PMS 3003	65 × 42 × 23	5 V DC	120	12.60	0.3–1	0–500 μg/m^3
Sharp GP2Y1010AU0F	46 × 30 × 18	5 V DC	20	10.6	>0.5	0–600 μg/m^3
Traditional PM measurement stationsModel	**Size (mm)**	**Output signal**	**Power consumption**	**Cost (EUR)**	**Particle diameter size (μm)**	**Concentration range of measurement**
ZM Sensor WXA100-08	160 × 160 × 290	12–24 V DC	0.36 W	1330	0.5–1	0–1000 μg/m^3
GRI-IAT	340 × 235 × 220	GPRS(Standard), RS485(Optional)	NA	3990	1	0–1000 μg/m^3
LPC PM10/PM2.5 Series 500	195 × 122 × 54	12 V DC	0.96 W	4440	1	0.1–1000 μg/m^3
Comde-Derenda APM-2	320 × 560 × 270	230 V AC	80 W	44375	1	0–1000 μg/m^3
Air pointer PM station	1200 × 782 × 615	230 V AC	1100 W	44375	1	0–25000 μg/m^3

Table 2
Cost of the replicated monitoring system with 14 sensor nodes and 1000 m^2 coverage area.

Coverage area (m^2)	Radius range (m)	Number of sensor nodes	Total cost (EUR)
1000	80	14	807

Therefore, in the total cost per day for 1000 sensor nodes total of seven routers are considered.

In future developments, the sensor monitoring system can be integrated with temperature and humidity sensors that will provide data for irrigation and plant nutrition, enabling development of solutions for automation of the irrigation and nutrition processes. Furthermore, the temperature sensor may be used to evaluate the thermal regulation impact of green wall systems.

2.3. Statistical tools

For the analyses of the measured data, a set of statistical tools have been applied, such as: kurtosis, skewness, coefficient variation, cross-correlation, Friedman test (Friedman (1937)), Mann-Whitney test (Mann and Whitney, 1947) and appropriate post hoc tests. These tools are used to determine mean, variance, maximums and minimums for various observed periods, distribution and regularity, statistically significant differences between measurements and correlations. The set builds coherent and appropriate methodology for assessing the influences of various factors on PM concentrations.

The coefficient of variation is the ratio of the standard deviation to the mean and it is proportional to the level of dispersion around the mean, i.e., higher coefficient of variation implies greater level of dispersion. When the coefficient of variation is near zero, it shows that there is no variability of the data set. This phenomenon can be considered as a constant in the period of observation.

The shape of the probability distribution can be described by two similar concepts known as kurtosis and skewness, which both measure the deviation from normal distribution of a random variable. A distribution can deviate from normal distribution in two ways: lack of symmetry and pointiness, known as skewness and kurtosis, respectively. Kurtosis is a measure of each time the data shows a flattening or an elongation from the normal density distribution of the random variable. This measure refers to the degree to which the data cluster in the tails of the distribution. Hence, the result is related to the tails of the distribution, but not to its peaks. Any univariant normal distribution has kurtosis equal 3, and therefore it is common practice to evaluate excess kurtosis instead of kurtosis, i.e.:

$$\text{excess kurtosis} = \text{kurtosis-3} \tag{1}$$

When the excess kurtosis has high values, the density distribution is concentrated around the mean. This indicates that there is regularity of the quantity values during the observed period.

The skewness is similar measure to the kurtosis. It measures the asymmetry of the density distribution of a random variable with respect to its mean. The most frequent data in skewed distributions are clustered at one end of the scale. If the skewness has near zero value, then the maximum probability coincides with the mean value. If the maximum probability is lower than the mean value, then there are high number of extreme values in the period of observation. This situation is described by positive skewness. When random variable has excess kurtosis and skewness above or below 0, then this indicates deviation from normal distribution. The similarity of two random variables is measured by cross-correlation.

In order to determine whether the difference between considered conditions is significant, usually the ANOVA test is performed. This test is a collection of statistical models used to analyse the differences among variable means, and it can be performed when the variables have normal distribution (Fisher, 1921). If the variables do not have normal distribution, non-parametric tests are perfumed. The Friedman test (Friedman (1939)) is the non-parametric alternative to the one-way ANOVA test. To determine whether any of the differences between the means are statistically significant, the significance level is set to $\alpha = 0.05$. A significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference. The null hypothesis, H_0, states the following:

$$H_0\text{: There is no difference between the conditions.} \tag{2}$$

The Friedman test determines a p-value for the given data. Then the obtained p-value is compared to the significance level α. If the p-value $\leq \alpha$, the Null hypothesis H_0 (2) is rejected i.e. the differences between the considered conditions are not statistically significant. If the p-value $> \alpha$, then the Null hypothesis H_0 (2) is confirmed, i.e. the differences between the conditions are statistically significant. When the Null hypothesis is rejected, i.e. the test reports significant difference between the conditions (variables) and if there are three or more different conditions, a post-hoc Friedman test (Friedman (1940)) should be performed. This test comparers the conditions (variables) in pairs and locates the difference. The post-hoc test Friedman test is similar to the Kruskal-Wallis test described in (Siegel and Castellan, 1988). This test takes the absolute value of the difference between the mean ranks of the different groups. Then it compares these differences to a value based on the value of z (corrected for the number of done comparisons), and constant based on the total sample size N and the number of conditions k. The purpose is to test if the inequality (3):

Table 3
Total cost per day for the sensor monitoring system.

Per day:	Sensor node			Wireless Router	Total cost per day
	PM10 and PM2.5 sensors	*CO and NO_2 sensors*	*Microcontroller ESP32-WROOM-32D*	*Cisco IEEE 802.11n standard*	*Total cost for the sensor system*
power consumption (W)	2.4	1.9	3.6	10	17.9
costs for single sensor (EUR)	0.0133			0.0168	0.0301
costs for 3 sensor nodes (EUR)	0.0399			0.0168	0.0567
costs for 100 sensor nodes (EUR)	1.33			0.0168	1.3468
costs for 1000 sensor nodes (EUR)	13.3			0.1176	13.4176

$$|\overline{R}_u - \overline{R}_v| \geq z_{\alpha/k(k-1)} \sqrt{\frac{k(k+1)}{6N}} \quad (3)$$

holds.

Another non-parametric modification of ANOVA test is the Mann-Whitney test (Mann and Whitney, 1947). Similar to the Friedman test, it is performed when variables are not normally distributed, but the test is done for two independent conditions.

3. Results and discussion

The measurements have begun in May 2018. Previous analyses (Srbinovska et al., 2017) have shown that the pollution in spring and summer is lower than the pollution during the winter months. This paper presents the measurements of PM2.5 and PM10, for the period from the 5th of December to the 19th of February, aiming to show the concentrations during the winter months. The next subsections present obtained measurement results and statistical analysis of the data.

3.1. Experimental measurements

The graphs on Fig. 2 and Fig. 3 present hourly average data for PM2.5 and PM10 concentrations respectively, encompassing a period of about 10 days, starting from 26th of December 2018 until 07th of January 2019, and serve to show typical winter days, with periods of high and low PM concentrations.

The graphs on Figs. 2 and 3 show that the peaks of PM2.5 and PM10 occur at the same time and that during the observed period there have been a number of such occurrences, each of them lasting for a few hours. As it can be observed by the graphs on Figs. 2 and 3, some of the measurements expected from node 2 are missing. The problem usually occurs because the node fell unexpectedly into silent mode or because problems in the wireless data transmission. In any case, the node has to be restarted, bearing in mind that some of the data is missing.

The graphs on Fig. 4 and Fig. 5 present the average data for concentrations of PM2.5 and PM10 during the week from 15th of January 2019 until 23rd of January, which is the week when the highest PM concentrations have been measured, considering the whole observed period (5th December – 19th February).

A more detailed representation of the observed week is represented in Fig. 6 - Fig. 9. Namely, Figs. 6 and 7 show the day of the week with the highest concentrations of PM2.5 and PM10, while Fig. 8 and Fig. 9 show the days of the same week, but with relatively low PM concentrations. Actually, the graphs on Figs. 6 and 7 present the day with highest measured 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 19th of January 2019. These values are observed at the sensor node 1, i.e. the node that is positioned the furthest away from the greenery.

The graphs presented on Figs. 8 and 9 show that the period with low PM concentrations lasted more than two days, when all nodes measured PM2.5 and PM10 concentrations with values less or about 20 μg/m^3 almost throughout the whole observed period. The graphs also show that this period of low PM concentrations is followed by a period of increase of the PM concentrations, occurring on 16th January, during the afternoon and night hours. However, the concentrations are not as high as the concentrations presented on Figs. 6 and 7.

The analyses of the campaign indicate that the measurements at the sensor node 3 show relatively lower values for the PM concentrations than the sensor node 1, which is the node that is located furthest from the green area. The sensor node 2 shows values that are close, at some points even slightly higher than the values measured at node 1. The average values presented on the graphs from Figs. 6–9 show that the differences in measured values are larger for the periods of the high PM concentrations and lower for the periods with low PM concentrations. The collected data confirms that the location of the measurement node and its relative position to the green infrastructure influences the measured PM concentrations. This can be supported by observing measured data from locations around Skopje from the online database (Jovanovski, 2020), where the measured values for days with high PM concentrations may differ for more than 20–50 μg/m^3 from one location to another, but the trends are generally the same – showing periods with high, moderate or low concentrations of PM2.5 and PM10. The measurements taken within this measurement campaign indicate that the location of the node, the adjacent objects and the existence of green areas have an influence on the PM concentrations. However, to increase the confidence in the interpretation of the results, the set of statistical tools presented above have been used. The statistical analyses of the collected data presented in the following section show the relation between various factors that influence the PM concentrations.

3.2. Statistical analysis of the measured data

The statistical data are calculated and analysed for the whole period 5th December 2018–19th February 2019. The descriptive statistics are also calculated for daytime and night-time. As a result,

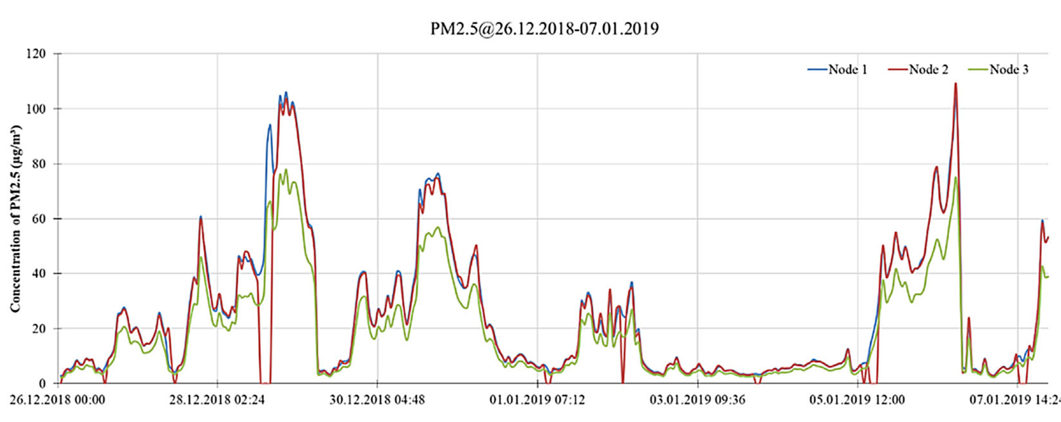

Fig. 2. Concentration of PM2.5 for 13 days, average hourly data.

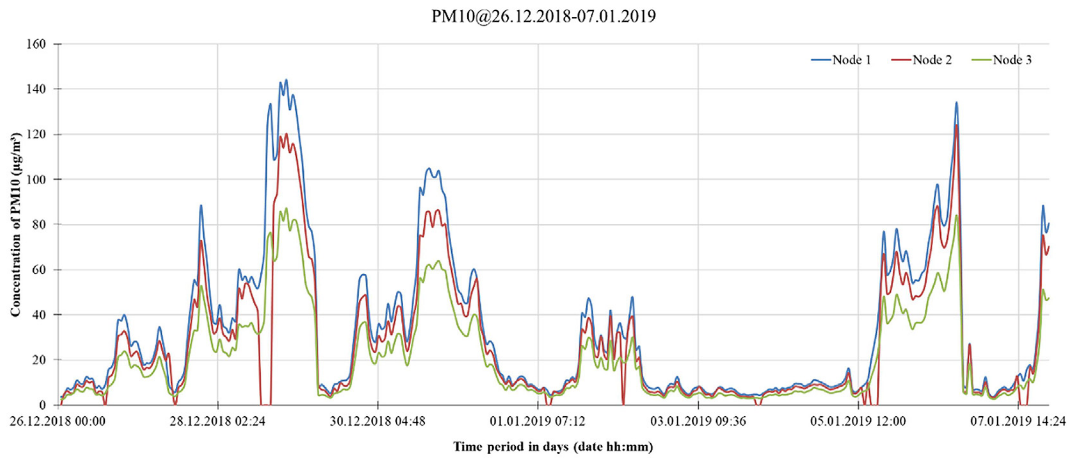

Fig. 3. Concentration of PM10 for 13 days, average hourly data.

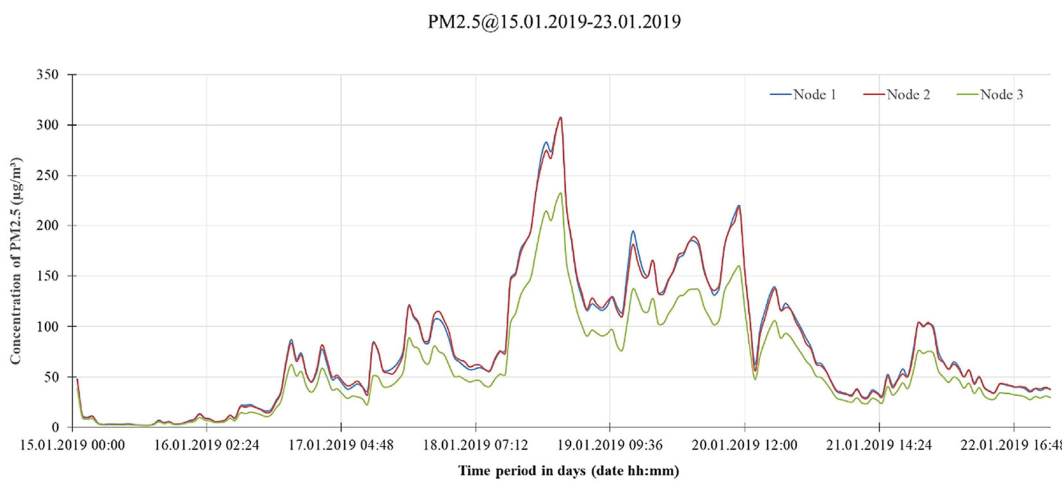

Fig. 4. Concentration of PM2.5 for one-week, average hourly data.

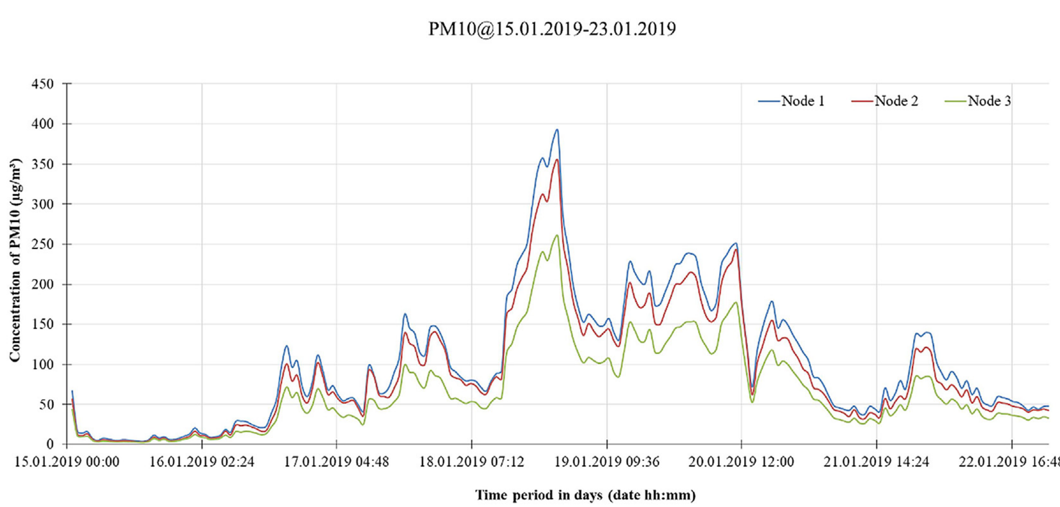

Fig. 5. Concentration of PM10 for one-week, average hourly data.

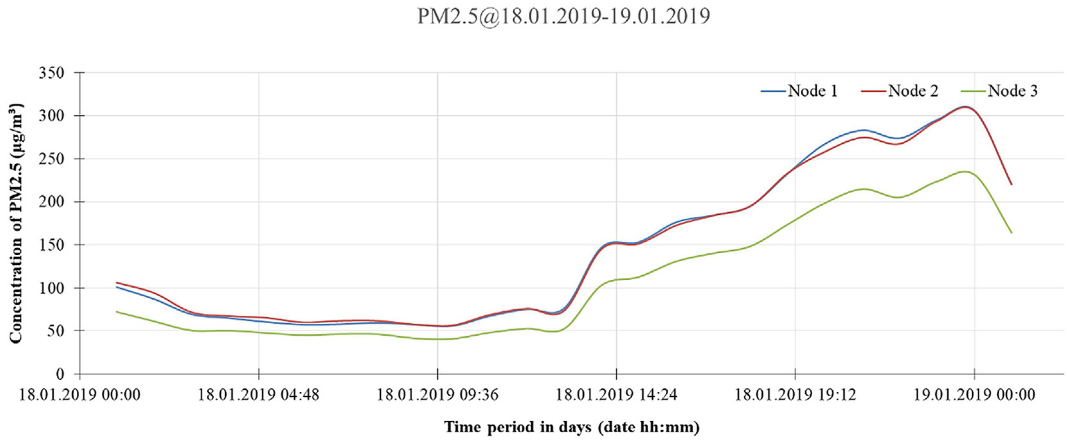

Fig. 6. Concentration of PM2.5 for 25 h, average hourly data.

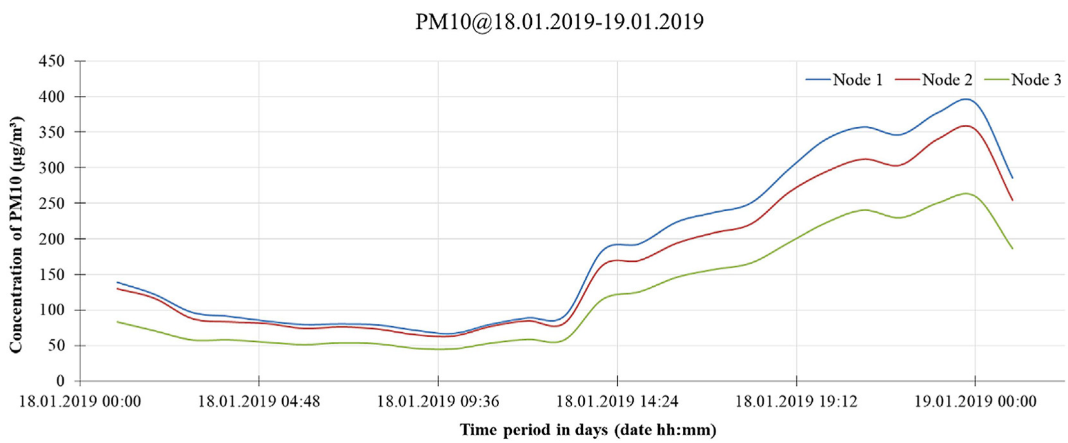

Fig. 7. Concentration of PM10 for 25 h, average hourly data.

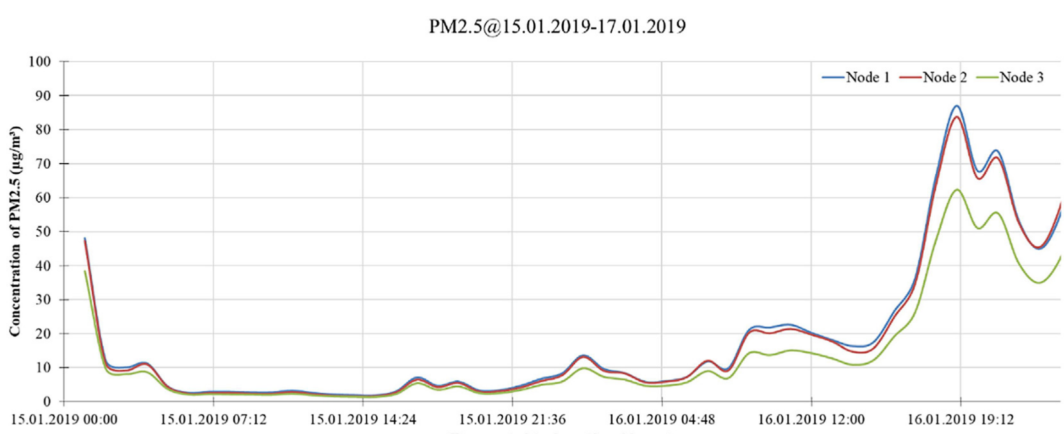

Fig. 8. Concentration of PM2.5 for 2 days, average hourly data.

the data presented in Table 4 show 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.). These periods have been chosen for two reasons – the period from 8 a.m. to 8 p.m. is the period of the day when there are activities within the faculty zone and thus movement is expected from both people and vehicles in the near vicinity of the experimental set up. The period from 8 p.m. to 8 a.m. is usually related to peaks in PM concentrations (Table 4) which are not directly caused by the activity at the faculty zone, but rather are related to other sources. The pollution sources and the chemical analyses of the pollutants are not in the scope of the research.

The statistical analysis of the data for PM2.5 and PM10 indicate that the data obtained in the observed period (during the whole

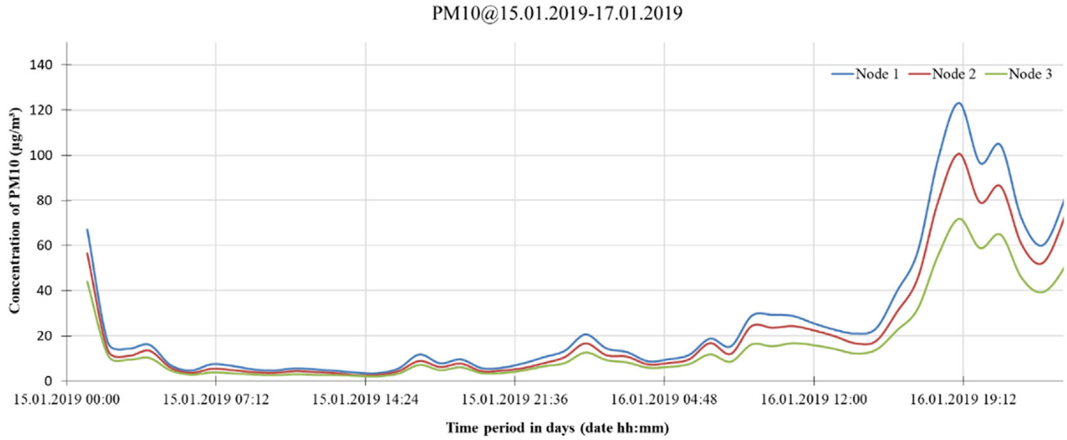

Fig. 9. Concentration of PM10 for 2 days, average hourly data.

Table 4
Descriptive statistics for the period 5 December 2018 to 19 February 2019, 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		
		Node 1	Node 2	Node 3	Node 1	Node 2	Node 3
Mean	i)	36.87	37.28	27.75	50.52	44.51	31.99
	ii)	34.68	34.94	25.76	47.08	41.35	29.63
	iii)	40.91	41.31	30.89	56.34	49.49	35.73
Maximum	i)	306.21	305.59	231.53	391.37	354.10	259.87
	ii)	267.25	258.22	198.55	340.29	294.71	222.68
	iii)	306.21	305.59	231.53	391.37	354.10	259.87

measurement period, daytime and night-time) does not have normal distribution. High values of excess kurtosis are reported in all considered cases (more than 5.86 for PM2.5 and more than 4.39 for PM10) which indicates regularity of the collected data in the observed period. At the same time, the positive values of skewness (approximately 2 for all considered cases for PM2.5 and PM10) indicate that there is a high number of extreme PM2.5 and PM10 concentrations measured in the observed period (in whole measurement period, daytime and night-time).

The results from the descriptive statistics for the whole period (Table 4) are also visualized in Fig. 10 and Fig. 11, showing that the considered data does not have normal distribution (the box presents 50% of the obtained data, the horizontal line in the box is the median of the corresponding data). The extreme concentrations of PM2.5 and of PM10 in the whole measurement period, suggested by the positive value of skewness, are presented by a star sign in Figs. 10 and 11, respectively. Each star represents a data sample for the measured data.

The cross correlation between measured PM2.5 and PM10 concentrations shows that there is a strong positive correlation (>0.98) between the concentration of PM2.5 and PM10 obtained from each node. Thus, what was observed as a characteristic from Figs. 2–9, is confirmed with the statistical analyses performed on the observed data set. Similarly, statistical analyses of the measured data show positive correlation between the humidity and the concentration of PM particles (>0.4). There is negative correlation (<-0.229) between temperature and concentration of PM particles and negative correlation between wind speed and PM pollution (<-0.43). Although humidity should have a positive impact on the decrease of PM concentrations, the low temperatures in the winter months and the disposition of the city have an adverse effect. It is observed that in the considered period the average temperature is 1 °C, the minimum temperature is −12 °C and the maximum temperature is 17 °C. The humidity in the observed period is between 29% and 100%, while the average humidity is 79.36%. The distribution of humidity and temperature data is close to normal. The wind speed is not normally distributed (excess kurtosis = 3.34 and skewness = 1.7). In the observed period there were days without wind (wind speed = 0 m/s), the maximum observed wind speed was 10 m/s and the average wind speed was 1.36 m/s.

3.3. Hypothesis tests

The data presented in Table 4 indicates differences of the descriptive statistical data for node 3 and the other two nodes. The same conjecture is imposed by the graphs presented from Figs. 2–7. As already mentioned above, it is obvious from Table 4, Figs. 10 and 11, that there is a difference in the mean of the data of PM2.5 and PM10 obtained from node 3 compared to the other two nodes. As the data has deviations from normality, a Friedman test was performed to confirm or reject our hypothesis.

The performed Friedman test for the data for PM2.5 and for PM10 results with p-value equal to 0 (χˆ2 (2) = 0, as the degree of freedom in this case is 2), and therefore there is statistically significant difference between the results obtained on different measurement locations. From Table 5 and from the average rank of the results for PM2.5, the rank mean values of node 1, node 2, and node 3 are 2.66, 2.31, and 1.01, respectively (rank 1 is assigned to the node that measured the lowest concentration of PM2.5, while rank 3 is assigned to the one that measured the highest PM2.5 concentration). Therefore, it can be concluded that node 3 has measured the smallest concentration of PM2.5 particles. The node 3 is the node located closest to the green area. Similarly, for PM10, the obtained rank mean values are 2.96, 2.03, and 1.01 for node 1, node 2 and node 3, respectively. So, the same conclusion is deduced - the measured PM10 at the location of node 3 is statistically different. To

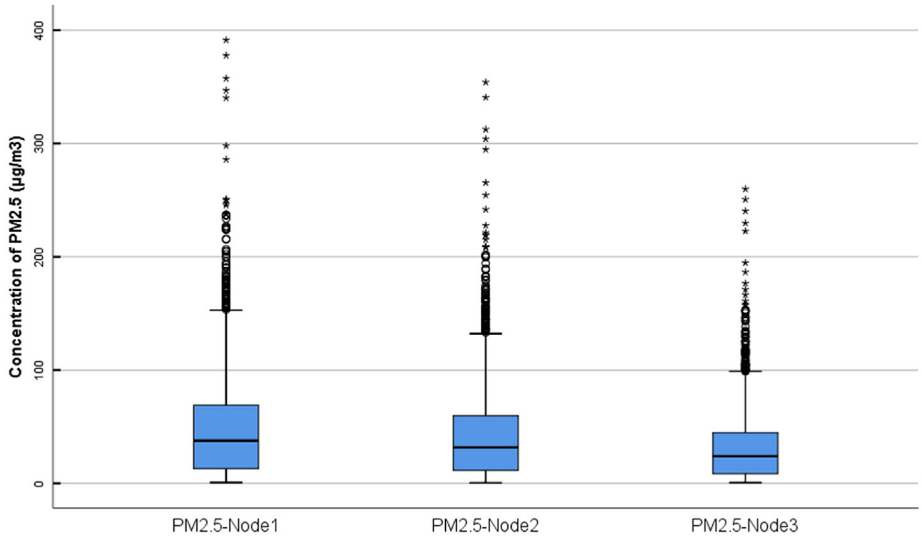

Fig. 10. Visualization of the descriptive statistics for PM2.5 in the period 5 December 2018 to 19 February 2019.

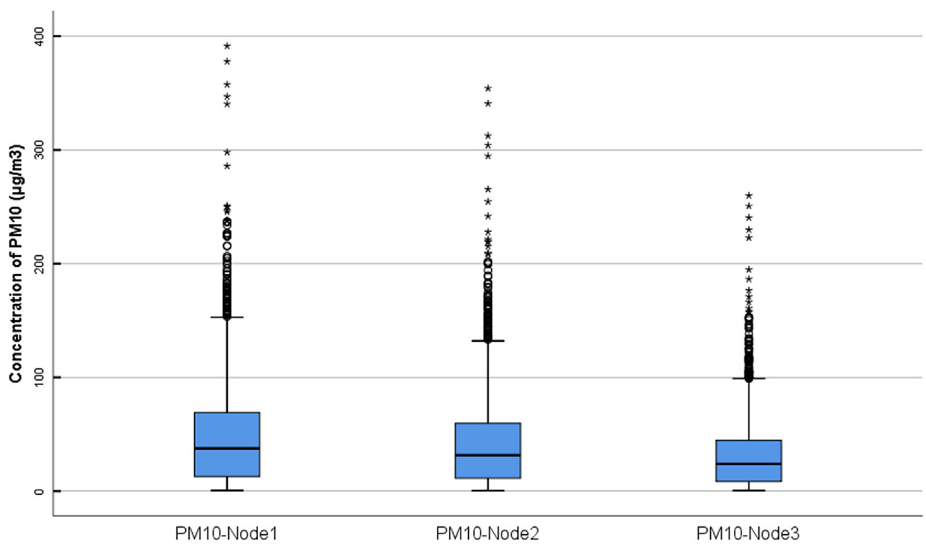

Fig. 11. Visualization of the descriptive statistics for PM10 in the period 5 December 2018 to 19 February 2019.

Table 5
Post – hoc test for Friedman's test comparing the difference between mean ranks of different groups.

Comparison	PM2.5			PM10		
	$\overline{R}_u$	$\overline{R}_v$	$\lvert\overline{R}_u - \overline{R}_v\rvert$	$\overline{R}_u$	$\overline{R}_v$	$\lvert\overline{R}_u - \overline{R}_v\rvert$
Node 1-Node 2	2.66	2.33	**0.33**	2.96	2.03	**0.93**
Node 1-Node 3	2.66	1.01	**1.65**	2.96	1.01	**1.95**
Node 2-Node 3	2.33	1.01	**1.23**	2.03	1.01	**1.02**

confirm these conclusions a post hoc Friedman test (Friedman M. b., 1940) was performed.

Let's set, as usual, $\alpha = 0.05$. In the studied data $k = 2$, and $N = 1673$, so $z_{\alpha/k(k-1)} = 2.40$ and the critical value in (3) is

$$z_{\alpha/k(k-1)}\sqrt{\frac{k(k+1)}{6N}} = 0.083. \tag{4}$$

The obtained results are given in Table 5 as the difference between all mean ranks $|\overline{\boldsymbol{R}}_{\boldsymbol{u}} - \overline{\boldsymbol{R}}_{\boldsymbol{v}}|$. This difference is higher than the critical value calculated in (4), which means that the difference is statistically significant. These results not only confirm our hypothesis that concentration of PM2.5 and PM10 is significantly lower at node 3, but also that the concentration of PM (both PM2.5 and PM10) is significantly lower at node 2 than at node 1.

This finally supports the observation that the difference between the measured data is related to the location of the nodes, the node furthest from the green area showing highest measured PM concentrations. The data for the comparison of nodes 1 and 2 also show a statistical difference, which can be considered as significant, but not to that extent as when nodes 1 and 3 are compared. However, it also confirms the previously stated, i.e. that the location of the nodes and their relative position towards green areas (with and without trees) and other adjacent objects has an impact on the measured PM concentrations. This implies that the placement of green walls as a measure for PM mitigation is a preferable when there is no possibility to develop green areas (zones with deciduous trees and evergreens).

The result from the descriptive statistics presented in Table 4 suggest that there is a difference in the concentration of PM during daytime (from 8 a.m. to 8 p.m.) and night-time (from 8 p.m. to 8 a.m.). Since many sources of pollution, such as traffic, heating and construction work, are inactive in the period from 8p.m. to 8 p.m., it is expected that the PM concentration during night-time should be smaller. The results in Table 4 suggest the opposite. This indicates another source of pollution that is non-active during daytime and indicates that further measurements on the chemical compound of the pollutants should be considered.

In order to verify if the observation is significant, the null hypothesis is tested under this condition. Since the data is not normally distributed, a nonparametric test is used. In this case, it is the Mann-Whitney test (Mann and Whitney, 1947), for two independent conditions. The asymptotic significance for these tests and the effect size are given in Table 6. The asymptotic significance is much smaller than $p = 0.05$, and therefore the null hypothesis is rejected, i.e., there is statistically significant difference between the concentration of PM during daytime and night-time. The effect size, as shown in Table 6, is small to medium (bellow 0.3). Therefore, it can be observed that the effect of the polluting sources which are active during night-time is much higher. As discussed above, the trend of the PM pollution during night-time in the observed period is not typical for the measurement location, but for the whole city.

From the graphs and descriptive statistics calculated for the observed period, it is clear that the sensor node 3 shows lower values of PM concentrations (both PM2.5 and PM10). Still the difference between this node and the other nodes, i.e. node 1 and node 2, is much more obvious in the periods of extreme PM concentrations (higher than 50 $\mu g/m^3$ for PM2.5 and higher than 100 $\mu g/m^3$ for PM10). Next table, Table 7, shows the descriptive statistics for normal (according to the World Health Organization (WHO)) and extreme PM2.5 concentrations. Similarly, Table 8 shows the descriptive statistics for normal (according to the WHO) and extreme PM10 concentrations. The ranking of the values in both cases is made with respect to node 1. The maximum at node 2 is higher than at node 1 and higher than the allowed 25 $\mu g/m^3$. As the ranking is made with respect to node 1, the value at node 2 is included in the set for the normal values.

From the data presented in Tables 4 and 7, it can be concluded that the concentration of PM2.5 is approximately 25% lower in node 3 than in node 1 in all the considered situations. Related work shows that in controlled environment with specific vegetation, the peak PM concentrations can be reduced up to 71.4% compared to environment without vegetation. In Leicester, the deposition of PM2.5 by trees and grass was observed to be 2.8% and 0.6% respectively (Jeanjean et al., 2016). The combined effects of green wall and green area in the vicinity of node 3 lead to almost 25% reduction of PM2.5 compared to the node 1, which has only grass patches in its vicinity. In the whole considered period, the pollution with PM10 at location 3 is reduced for 37%. The concentration of PM10 in node 3 is 35% lower than in node 1 in case of normal concentration (<50μg/m3), and even 43.5% in the periods of extreme concentration (Table 8). Related work shows PM10 reduction up to 23% in urban canyons (Radić et al., 2019), which is lower than on more open urban areas. The analyses imply that the location of the nodes, i.e. their position closer to the green areas and other objects, influences the measured concentration of PM. However, the extent of each of these influences cannot be clearly identified with the available data. Furthermore, the influence of the location on PM10 is higher than on PM2.5. This can be observed by the descriptive data in Tables 7 and 8.

Table 6
Mann- Whitney test comparing the pollution during daytime and night-time.

	PM2.5			PM10		
	Node 1	*Node 2*	*Node 3*	*Node 1*	*Node 2*	*Node 3*
Asymp. Sig. (2-tailed)	0.002	0.004	0.000	0.001	0.002	0.000
Effect size	0.102	0.097	0.12	0.11	0.104	0.126

Table 7
Descriptive statistics for the period 5 December 2018 to 19 February 2019, for normal and extreme values of PM2.5.

	Normal values, <25 $\mu g/m^3$			Extreme values, $\geq$50 $\mu g/m^3$		
	Node 1	*Node 2*	*Node 3*	*Node 1*	*Node 2*	*Node 3*
Mean	10.30	10.32	7.86	87.76	87.96	65.64
Sample Variance	39.82	40.10	22.93	1609.86	1668.63	913.92
Count	840	773	838	443	422	441

Table 8
Descriptive statistics for the period 5 December 2018 to 19 February 2019, for normal and extreme values of PM10.

	Normal values, <50 $\mu g/m^3$			Extreme values, $\geq$100 $\mu g/m^3$		
	Node 1	*Node 2*	*Node 3*	*Node 1*	*Node 2*	*Node 3*
Mean	21.32	18.40	13.86	150.98	133.13	93.98
Sample Variance	207.76	163.59	88.82	2234.88	2025.08	1131.08
Count	1143.00	1038.00	1140.00	255.00	238.00	254.00

The results from the measurements undertaken during the winter months (December 2018–February 2019) confirm the high concentrations of PM2.5 and PM10 on the micro-location, which is in line with measurements from data bases located around the city of Skopje. The measured data shows typical occurrence of high PM concentrations in specific parts of the day which is a trend observed on the various measurement locations throughout the city as well. There is a strong positive correlation between the PM10 and PM2.5 concentrations, which is not typical just for the observed location, confirms the initial hypothesis of the research. This is quite important when designing measures for PM mitigation as well as when developing air pollution prediction tools.

While the experimental results are specific for the location, the conclusions and statistical analyses undertaken to assess the measurement location relative to the green infrastructure can be generalized to derive the following conclusions. Firstly, the influence of green infrastructure on PM concentration under the described conditions is significant, as shown by the applied statistical analysis. Moreover, the differences in measured values obtained by measurement nodes positioned in relatively small distances are not negligible, thus implying that the relative position of the measurement nodes to the green infrastructure influences the measured PM concentrations. Therefore, the measurement location should be carefully considered for any air quality monitoring system and that measurements with higher spatial granularity should be used for modelling and air quality forecasting purposes. As a result of the analyses, it can be concluded that statistical evaluation of measured data and assessment of the location and its surroundings should be considered prior placement of a green wall. By doing so, maximum effects of the green wall on PM concentration decrease can be expected.

Considering the influence of meteorological factors, the established correlations are specific to the location, showing that wind speed has the highest influence on PM concentrations, followed by humidity and temperature. Generalization of the observed correlations lead to the conclusion that combination of low temperatures, high humidity and no, or low wind speed lead to high PM concentrations.

3.4. Decision-making supportive tool

With the aim to increase the practicality of the described system and to contribute to the increase of the capacity of local governments in dealing with air pollution, the results and findings discussed above are organized in a decision-making supportive algorithm. The algorithm is presented in Fig. 12 and it basically streamlines the discussions above into a set of steps that can be undertaken when discussing solutions for PM mitigation. The presented algorithm takes in consideration that green walls, as the one described in this paper, represent simple and affordable solutions for PM concentration mitigation. It also considers that long-term measures should include planting green tree zones that have a higher impact on PM mitigation, especially considering extreme levels of PM. The process starts with inputs from measurements on air quality and inputs from decision-making stakeholders. The latter may be results of public debates with non-governmental sector and local community, questionnaires to assess the public opinion and acceptance for certain measures, investigations on pollutants and activities of inspection bodies and other inputs. By statistical analyses of the data using the methodology described in this paper, the average concentrations of PM can be derived. The statistical tools enable the users to consider the specifics of the location and other external factors (high level concentrations occurring at certain times of the day or meteorological influences), i.e. introduce high confidence in the calculated and analysed data. The algorithm compares the statistically obtained data to the reference categories from WHO (from very low to very high, with reference to PM2.5, as depicted in Fig. 12). This can be justified by the observed very high correlation of PM10 and PM2.5 and the fact that PM2.5 has worse impact on human health.

Considering the presented algorithm, measures should be undertaken when the average concentrations observed in a designated period are higher than medium. In such cases, the spatial conditions for planting trees (developing urban green zones) are investigated and based on that and the availability of financing, the appropriate action is taken, as recommended by the algorithm. For the cases of high and very high levels of PM, the tool advises urgent implementation of green walls and working on creating conditions for planting trees. The condition for checking the occurrence of pollution at night-time, followed by actions to determine the sources of pollutants is related to the specifics of Skopje and generally, the situation in North Macedonia. However, this condition does not decrease the generality of the algorithm, as it can be replaced with some other, which is relevant for another location, or can be discarded.

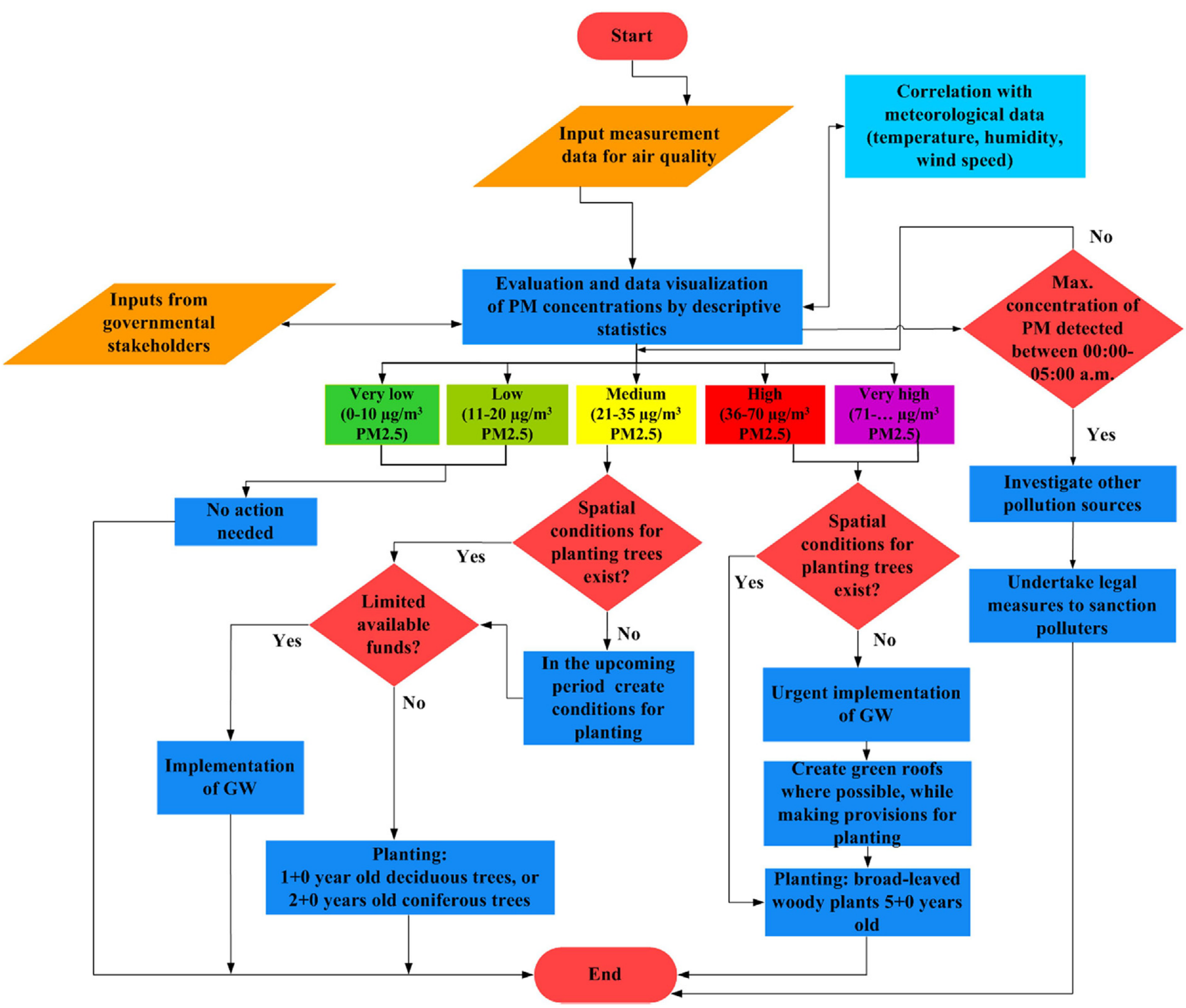

Fig. 12. Decision-making supportive tool.

4. Conclusions

The paper describes a low-cost green wall structure and WSN PM concentration measurement system, which has high scalability and replicability. The developed system provides quality data that can be further processed with the described statistical tools to evaluate the influence of green infrastructure on PM concentration.

The implementation of green infrastructure and the possibility to evaluate its effect on PM mitigation provide multi-fold effects on communities. Experimental setups, as the one described in this paper, serve to derive a set of successive steps that need to be undertaken to reduce PM concentrations. These steps should be taken both by governmental bodies and citizens living in urban areas. This paper shows an example how “environmentally conscious” approach in developing solutions and using advanced technologies can bring benefits to local communities. The decision-making supportive algorithm presented in this paper uses sound methodology and statistics in analyses of data so that the solutions for decreasing PM concentrations can be proposed with high confidence in their effectiveness. The described algorithm takes in consideration local conditions, but without loss of generality, which makes it a candidate tool for application under various conditions. Furthermore, the low-cost and replicable WSN system described in this paper shows potential for wide-scale implementation, which is essential for any engineering solution. The specifics of the system can be easily customized to the needs of the users and the location. The storage of collected data to an open access cloud platform provides easy access and sharing of data for further analyses. The proposed solution can be further improved with new sensors for humidity and temperature which can be used for developing irrigation and plant nutrition solutions for the green wall. The indirect effects of such systems encompass improved health of citizens living in urban areas and raised public awareness on the negative impact of air pollution and waste. This effect should not be neglected for the regions where the general public is not fully aware of the risks and consequences of air pollution. As shown in this paper, the green infrastructure, including green walls may be designed from discarded materials and thus, contribute to reduction of urban waste.

The results discussed in the previous section show that location of green infrastructure in urban environments should be carefully planned in order to maximise its effect on air quality. This statement is supported by the fact that the differences in measured values obtained by measurement nodes positioned in relatively small distances are not negligible. This implies that the relative position of the green wall to other objects/urban equipment and green zones influences its effect on PM mitigation. The results and discussions presented in this paper are valuable in making decisions on granularity of spatial and temporal data when designing air pollution prediction systems. Our findings suggest that granularity of data, especially for dense urban areas with green infrastructures that vary in size and density, are essential to provide a good quality prediction model.

CRediT authorship contribution statement

Mare Srbinovska: Conceptualization, Methodology, Writing - original draft. **Vesna Andova:** Formal analysis. **Aleksandra Krkoleva Mateska:** Writing - review & editing. **Maja Celeska Krstevska:** Formal analysis, Writing - review & editing, Visualization.

Declaration of competing interest

None.

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