AIR QUALITY INVESTIGATION IN URBAN PARKS USING NEURAL NETWORKS

P. Savov, V. Hristov, S. Topalov

University of Mining and Geology “St. Ivan Rilski”, 1700 Sofia; e-mail:psavov@mgu.bg

ABSTRACT. Streets with heavy traffic often surround urban parks and increase the potential user exposure to air pollutants from vehicles. Particulate matter (PM) is directly associated with the deterioration of air quality and with environmental and health effects. It has been established that in the downwind direction, pollutant concentrations decrease rapidly from the roadside and within some dozens of meters reach relatively constant values. An even sharper gradient is found in the upwind direction, with a rapid increase of the distance from the road edge. This study is designed to investigate the correlation between PM concentration in urban parks, meteorological parameters (temperature, humidity, wind speed and direction), traffic intensity, and the density of trees in parks, using an artificial neural network model. Thus, from the perspective of human exposure to air pollutants in urban parks, this study provides observations of relevance for future park design in densely populated cities.

Key words: air quality, urban parks, neural networks.

ИЗСЛЕДВАНЕ НА КАЧЕСТВОТО НА ВЪЗДУХА В ГРАДСКИ ПАРКОВЕ С ПОМОЩТА НА НЕВРОННИ МРЕЖИ

П. Савов, В. Христов, С. Топалов

Минно-геоложки университет „Св. Иван Рилски“, 1700 София

РЕЗЮМЕ. Улиците с интензивен трафик често обграждат градските паркове и увеличават риска от излагане на гражданите на високи нива на замърсяване на въздуха от превозните средства. Фините прахови частици (ФПЧ) са пряко свързани с влошаването на качеството на въздуха и въздействието върху околната среда и върху здравето. Установено е, че по посока на вятъра концентрациите на замърсителите бързо намаляват от пътя и след няколко десетки метра достигат относително постоянни стойности. Още по-рязък скок се открива в наветрената посока, с отдалечаване от пътното платно. Това проучване има за цел да изследва връзката между концентрацията на ФПЧ в градските паркове, метеорологичните параметри (температура, влажност, скорост и посока на вятъра), интензивността на движението и плътността на дърветата в парка, като се използва модел на изкуствена невронна мрежа. По този начин, от гледна точка на излагането на човека на замърсители на въздуха в градските паркове, това проучване ще предостави ценна информация за оформяне на бъдещия дизайн на парковете в гъсто населени градове.

Ключови думи: качество на въздуха, градски паркове, невронни мрежи.

Introduction

Airborne particulate matter can represent a serious issue for human health, especially in densely populated urban areas. Moreover, the inhalation of particulate matter (PM) can be more harmful with the decreasing particle diameter. Vegetation can provide many ecosystem services to the citizens, including the removal of many different pollutants in the air (Pallozi et all., 2020)

Urban parks have long been considered places of refuge from the bustle, noise, and pollutants of the surrounding city. Parks were labelled the lungs of the city, a metaphor which gained support as studies revealed the deposition of pollutants to leaf surfaces (Xing and Brimblecombe, 2019).

The general relationship between vegetation and air quality in urban parks and cities has been widely researched (Xing and Brimbelcomb, 2020; Gymez-Moreno et al., 2016; Leunget al., 2011).

Most plants have a large surface area per unit volume, increasing the probability of deposition compared with the smooth, manufactured surfaces present in urban areas. For example, 10 - 30 times faster deposition has been reported for sub-micrometre (<μm) particles on synthetic grass compared with glass and cement surfaces.

Urban vegetation can also contribute to the reduction of the urban heat island effect, and trees have a clear role to play in microclimate amelioration.

Meteorology is another major factor in ambient PM concentrations since dispersion processes, removal mechanisms, and chemical formation of atmospheric particles depend on parameters such as wind speed, air temperature and humidity, and solar radiation. For this reason, some studies carried out in urban areas have investigated the relationship between meteorological variables and PM levels (Galindo et all., 2011).

In this work, we explore the dispersion pattern of traffic derived PM in urban parks under weak winds conditions (1 – 3 m/s) using both field measurements and statistical analysis.

Materials and methods

Site descriptions

The measurements of fine PM were carried out in the Student Park of the city of Sofia. It is located in the south-eastern part of the city, about 7 km from the center. The total park area is about 50 000 m². In general, the park is a grass area, and in some places there are tree plantations with a density of about 2-3 trees per 1000 m² In such an area marked with an asterisk on the map (Fig. 1) the measurements of the fine dust particles concentration were performed.

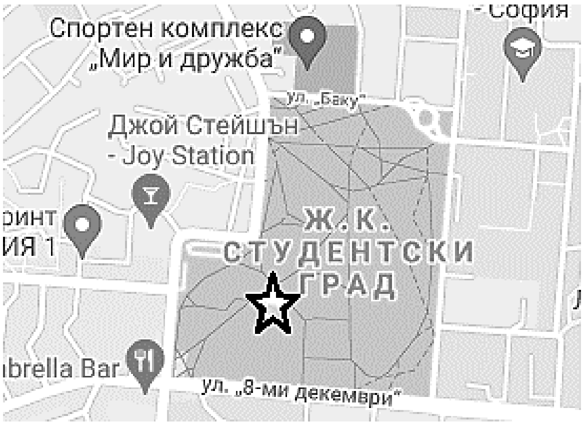

Fig. 1. Map of Studentski Park. The experiment place is marked with an asterisk.

Aerosol measurements

The campaign was carried out in September 2015 in clear weather and at relatively low wind speeds (2-3 m/s).

The measurements are time series of the particles concentration in 6 ranges of their radii. The frequency of measurement is every half hour in the course of 5 days.

A six-channel Met One (USA) LPC (laser particle counter) was used in the experiment. Particle size channels were 0.3, 0.5, 0.7, 1.2, and 5 µm. The accuracy of the devices was in the frame of 15-20%. The dimension was number of particles per 1 cubic meter of air for every channel.

Meteorological parameters were taken from Sofia Airport meteorological station.

Results and discussion

The following Fig. 2 shows the fine dust particle curves evolution for the whole measurement period for all five channels (the sixth channel for 0.3 µs is not shown because its values are very high and the other channels are strongly suppressed and would not be well shown in the figure).

It is clear from the graph that the difference between the number of the smallest (0.5 µm) and the largest (5 µm) particles is of the order of thousands with a difference in radius of 10 times only.

For almost the entire period, the particles number for all six channels did not exceed the limit values, with a few exceptions of the appearance of peak values for a very short time (these are some local short-term emissions).

The evolution of the curves does not show any clear periodic dependence. There is a round-the-clock movement of lows at night and highs during the day, mainly due to the intensity of road transport on the nearby boulevard. It creates two distinct peaks in the morning around 8 - 9 o'clock and in the evening at 18 - 20 o'clock. However, these peaks are best seen after the performed statistic analysis below.

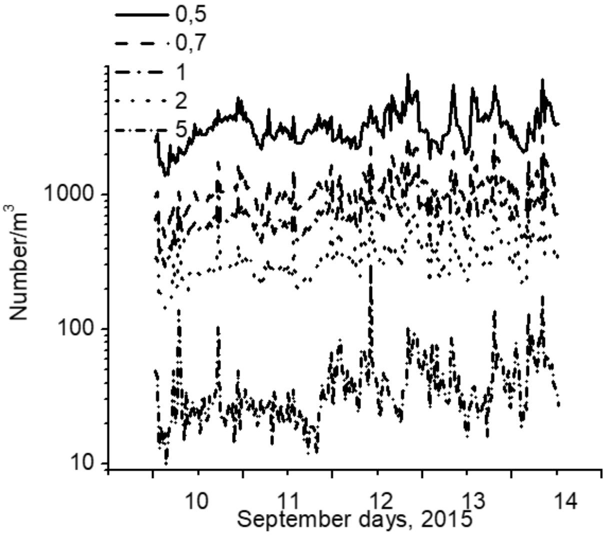

Fig. 2. Curves of the evolution of fine PM, measured in the period from 10 to 14 September 2015 for a range of radii from 0.5 to 5 µ.

Apart from transport, with its bimodal daily appearance, meteorological parameters such as wind direction and speed, temperature, and relative humidity also exert influence on the distribution of the particles number.

There are a number of works related to the research of the main meteorological parameters on the fine PM dispersion, but they are mainly performed in open urban areas.

The aim is to investigate these relations in more complex conditions - in a park area of the city.

Data analysis

From September 10th - 8 a.m. till September 14th - 11:27 p.m., 225 samples were taken in approximately every 30 minutes. The samples included the following data: time, six PM parmeters (0.3µm, 0.5µm, 0.7µm, 1.0µm, 2.0µm, and 5.0µm), temperature, humidity, wind direction, and wind force. Wind direction data of 12 samples are missing or incorrect.

The average values and the variance of the particle distribution are given in Table 1:

Table 1. *Average and Variance of the number of particles*

	0,3	0,5	0,7	1,0	2,0	5,0
Average	64280	3288	1165	751	355	40
Variance	18149	1044	387	262	143	29

Figure 3 shows a graph of the average values according to the particle size. The trend line shows that the average number of particles is distributed according to a precipitous exponential function, as the number of the smallest particles is many times larger than the larger ones. The probable reason for this may be that the smallest particles are emitted in the largest quantities, or that by the measuring point a significant part of the larger particles precipitate. If measurements are made at several different distances, this problem can be solved.

The particle distribution within one day shows a certain cyclicity (Figure 4) with peak values of about 8 and 19 hours, which corresponds to the peak values of traffic on the boulevard.

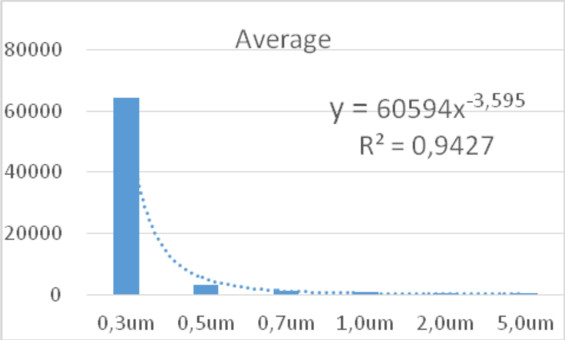

Fig. 3. Average values of the number of particles according to their size

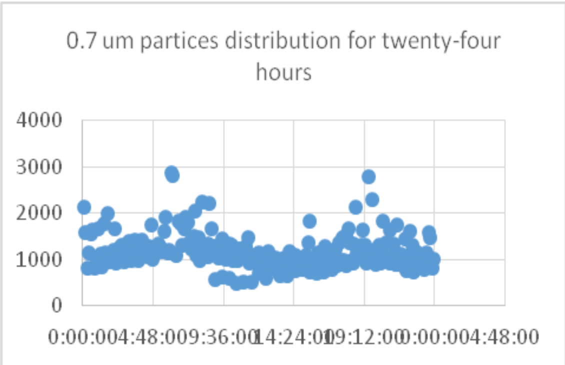

Fig. 4. Twenty-four-hour period particle propagation.

Figs. 5–7 show the correlation of the dependence between the number of particles and the temperature, humidity, and wind strength.

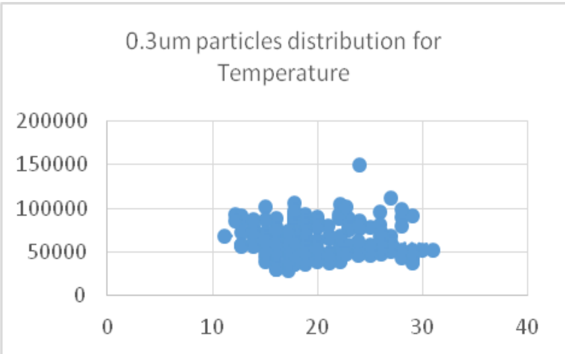

Fig. 5. Correlation between particle number and temperature

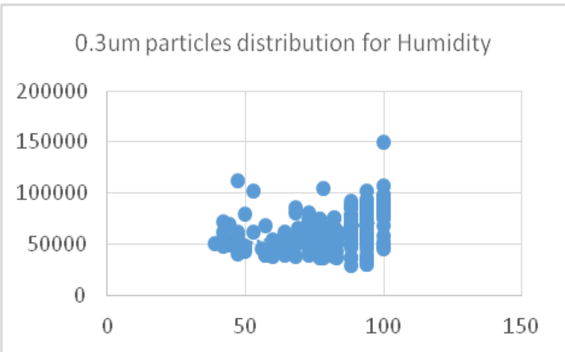

Fig.6. Correlation between particle number and humidity.

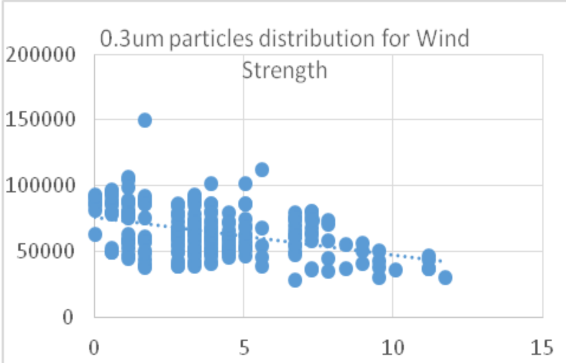

Fig. 7. Correlation between particle number and the wind speed.

The correlation coefficients between the data for 0.3µm and 0.5µm, between 0.5µm and 0.7µm, and so on, are shown in Table 2:

Table 2. *Correlations between particles of different sizes*

0.3 – 0.5	0.5 – 0.7	0.7 – 1.0	1.0 – 2.0	2.0 – 5.0
0.862	0.933	0.982	0.96	0.868

It can be seen that they are quite close to 1, which means that the particles propagate in the same pattern regardless of their size.

Table 3 shows the correlation coefficients of the dependence between the number of particles and the temperature, humidity and wind strength.

Table 3. *Influence of temperature, humidity and wind force on the number of particles*

	0,3 µm	0,5 µm	0,7 µm	1,0 µm	2,0 µm	5,0 µm
T[C]	-0.123	0.013	0.082	0.103	0.152	0.177
RH [%]	0.389	0.203	0.084	0.016	-0.099	-0.234
WS [m/s]	-0.404	-0.35	-0.319	-0.282	-0.21	-0.038

It can be seen that the particle distribution depends on temperature very slightly. However, there is a tendency: For the smallest particles (0.3µm), the dependence is inversely proportional (higher temperature - fewer particles). In the other cases, it is directly proportional, as the influence of temperature increases with the increase in particle size. Particle propagation is weakly dependent on humidity. The trend is that the relation on humidity strongly depends on the particle size. The dependence of the number of particles on the wind force is inversely proportional and decreases with the increasing particle size.

Training of neural networks

In (Hristov et al., 2015), the training of neural networks for forecasting the propagation of fine PM in the region of the towns of Stara Zagora - Galabovo is examined. There, however, the pollution of a large area with developed mining activity is considered.

The present study examines the distribution of fine PM within a city park depending on the traffic on a busy boulevard. *Multilayer Perceptron* (MLP) regression neural networks were trained using the *Statistica 12* software. The *Automation Network Search* (ANS) module was used. This approach sets the type of networks required and their basic parameters, and the system trains and tests a number of networks with these parameters and finally shows some of the best trained. There are two types of network in the system: MLP with one hidden layer, and RBF (*Radial Base Function*).

The network being trained has 5 inputs and 6 outputs. The analysis is set to search for the MLP and RBF regression networks with 10 to 20 nodes in the hidden layer and the number of searched networks (10), showing the results for the 5 best.

The network inputs are: weather, temperature, humidity, wind direction, and wind force. The outputs are the numbers of the corresponding 6 classes of particles of different sizes.

The purpose is to find a network on which, if specific data at the input are given, it can predict the numbers of these 6 types of particles.

The number of samples included in the analysis is 222. They are randomly divided approximately equally into a training and a testing sample.

After searching and training, the ANS module found the 5 best networks (4 - MLP and 1 - RBF). One of them, an MLP network, was selected and the data for it are given in Table 4:

Table 4. *Results of neural network training with 6 outputs*

Net. name	Training per-formance	Testing per-formance	Training algorithm	Hidden activation	Output activation
MLP 5-20-6	0.71346	0.5673	BFGS 92	Tanh	Identity

MLP 5-20-6 means: 5 input neurons, 20 neurons in the hidden layer and 6 output neurons.

Training performance means the correlation between the training target values and the values calculated by the network for the same input data.

Testing performance means the correlation between the test target values and the values calculated by the network for the same input data.

The two correlation coefficients differ by about 0.1, which means that the network is not overtrained. The value of the coefficients indicates that the result is acceptable but not excellent. A better result would be obtained if 6 separate networks with the same inputs were trained, but with one output for the number of one particle type.

BFGS 92 means the Broyden-Fletcher-Goldfarb-Shanno training algorithm with 92 training epochs.

The activation function of the neurons in the hidden layer is tanh.

The activation function of the output neurons is identity (linear function at 45 degrees angle)

The correlation coefficients showing the quality of training and testing of neural networks for the 6 types of particles are shown in Table 5:

Table 5.

0.3 train	0.3 test	0.5 train	0.5 test	0.7 train	0.7 test	1.0 train	1.0 test	2.0 train	2.0 test	2.0 train	2.0 test
0.846420	0.754003	0.795482	0.615036	0.751733	0.559153	0.715429	0.533206	0.648326	0.506868	0.523364	0.435416

The significance of the input parameters is shown in Table 6. It can be seen that time is the most important parameter and the others are of approximately equal importance.

Table 6.

Networks	Sensitivity analysis, Samples: Train				
	Time	Wind Strength	Wind Direction	Temperature	Humidity
3.MLP 5-20-6	4.43147	1.732203	1.4213	1.3800	1.3520

Figure 8 shows graphs of the actual data and the data calculated by the neural network for the number of particles with a size of 0.3µm. It is noticed that the biggest differences are in the extreme values.

Fig. 8. Graphs of the actual data and the neural network calculated data

Conclusion

The results of a study of the influence of the city park and the main meteorological parameters on the dispersion of fine PM (fine dust particles) in the atmosphere are presented in the paper.

Based on the experiment results and the statistical time series analysis, the following can be concluded:

1. The number of aerosol particles from the finely dispersed part of the spectrum in size (0.3 µm) exceeds the number of the coarsely dispersed part (5 µm) by over a thousand times;
2. In the statistical processing of the data, the two peaks in the diurnal course of the particle concentration are well outlined, mainly due to the maximum in the intensity of the automobile traffic in these intervals of the day;
3. It can be seen from the correlation analysis that the strongest dependence is observed between the particles number and the wind speed, as this dependence is negative, i.e. with the wind increasing, the number of particles decreases;
4. There is a significant decrease in the value of the correlation coefficient for temperature and humidity compared to the results conducted in an open terrain. This shows that the park area has a depressing effect on the influence degree of

these two meteorological parameters on the aerosol dispersion in the park atmosphere;

5. The results prove that the data of aerosol particle concentration measurements in the course of several days are sufficient to train a neural network well and can give good results in the dispersion simulation depending on meteorological conditions.

Acknowledgements. This work has been carried out within the framework of the National Science Program "Environmental Protection and Reduction of Risks of Adverse Events and Natural Disasters", approved by the Resolution of the Council of Ministers № 577/17.08.2018 and supported by the Ministry of Education and Science of Bulgaria (Agreement № D01-322/18.12.2019).

References

Galindo, N., M. Varea, J. Gil-Molty, E. Yubero, J. Nicolas. 2011. The Influence of Meteorology on Particulate Matter Concentrations at an Urban Mediterranean Location. - *Water Air Soil Pollut,* 215:365–372 DOI 10.100/s11270-010-0484-z

Gymez-Moreno, F., B. Artinano, E. Ramiro, M. Barreiro, L. Nunez, E. Coz, C. Dimitroulopoulou, S. Vardoulakis, C. Yague, G. Maqueda, M. Sastre, C. Roman- Cascon, J.M. Santamaria, R. Borge. - *Urban vegetation and particle air pollution: Experimental campaigns in a traffic hotspot.* PII: S0269-7491(18)34299-4 DOI: https://doi.org/10.1016/j.envpol.2019.01.016 Reference: ENPO 12055 To appear in: Environmental Pollution

Hristov V., R. Karakerezov, S. Topalov. 2015. Dust Air Pollution Predicting in a Mining Area by Artificial Neural Network. - *Annual of the University of Mining and Geology* “St. Ivan Rilski”, 58, Part II, Mining and Mineral processing.

Janhall, S. 2015. Review on urban vegetation and particle air pollution e Deposition and dispersion. - *Atmospheric Environment* ,105 130 e 137.

Leung, L., J. Tsui, F. Chen, W. Yip, L. Vrijmoed, C. Liu. 2011. Effects of Urban Vegetation on Urban Air Quality. - *Landscape Research*, 36, No. 2, 173–188, April 2011

Pallozzi, E., G. Guidolotti, M. Mattioni, C. Calfapietra. Particulate matter concentrations and fluxes within an urban park in Naples. - *Environmental Pollution.* PII: S0269-7491(20)31972-2, DOI: https://doi.org/10.1016/j.envpol.2020.115134, Reference: ENPO 115134

Vailshery, L., M. Jaganmohan, H. Nagendra. 2013. Effect of street trees on microclimate and air pollution in a tropical city. - *Urban Forestry & Urban Greening,* 12, 408–415.

Xing, Y., P. Brimblecombe. 2019. Role of vegetation in deposition and dispersion of air pollution in urban parks. - *Atmospheric Environment,* 201, 73–83.

Xing, Y., P. Brimblecombe. 2020. Urban park layout and exposure to trafc-derived air pollutants. - *Landscape and Urban Planning,* 194, 103682.