Design of an Urban Monitoring System for Air Quality in Smart Cities

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Abstract: Pollution is one of the main problems faced by cities nowadays, due to the increase in emissions from anthropogenic sources resulting from economic, industrial and demographic development. High values of pollutants, such as atmospheric particulate matter, lead to adverse effects on the environment and human health, causing the spread of respiratory, cardiovascular and neurological problems. For instance, recent work shows a connection between the spread of the Covid-19 pandemic and environmental pollution. In this context, urban monitoring of pollutants can allow to evaluate and perform actions aimed at reducing pollution in order to safeguard citizens' health. This study proposes a method to design an urban air quality monitoring system. It uses the AHP multi-criteria decision-making technique to define the initial positioning of the sensors, and the cellular automata mathematical model for the following optimization, from which the final configuration of the network is derived. In the present case study, the monitoring concerns atmospheric particulate matter (PM10 and PM2.5) and is carried out with six sensors that constitute a LoRaWAN network, as often used for monitoring activities in smart cities.

1 INTRODUCTION

The economic, industrial and demographic development of the last two centuries has led to a considerable improvement in the quality of human life, but it has caused at the same time significant consequences for the environment. Indeed, anthropogenic sources such as industrial processes, vehicular traffic and domestic heating are identified as the main causes of pollution (Samad & Vogt, 2020). According to World Health Organization (2006), four main air pollutants can be identified: particulate matter (PM10, PM2.5), nitrogen dioxide (NO2), sulfur dioxide (SO2) and ozone (O3). In the event that the concentrations of these pollutants reach high values, human health is likely to be compromised with the insurgence of respiratory, cardiovascular and neurological problems (Ghorani-Azam et al.,2016) and the balance of ecosystems is put at risk (De Marco et al., 2019). During the year 2016, according to the WHO, 91% of the world population lived in places where air quality did not meet the levels established by the guidelines; also in the same year, air pollution caused 4.2 million deaths worldwide. A reduction of particulate matter from 70 to 20 micrograms per cubic metre is estimated to reduce mortality by 15%, also lowering the incidence of diseases (*Ambient (outdoor) air pollution*, 2018). Kurt et al. (2016) studied the effects of pollution on the respiratory system and identified ozone and particulate matter as the main responsible of cardiopulmonary diseases. In particular, children have been found to be the most sensitive to pollution-induced effects. A study conducted on 265 children from two Indian cities with different levels of pollution found a greater amount of dysfunction in the respiratory tract in children with long-term exposure to high pollution values (De, 2020). Moreover, scientific research showed the role of pollutants in the spread of viruses, especially particulate matter. A more significant presence of the Avian Influenza Virus was identified in air samples collected during the days of Asian dust storms, when concentrations of PM10 and PM2.5 are higher. This showed the role

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of dust storms in the long-range transport of virus (Chen et al., 2010). Then, following the spread of the SARS-CoV-2 virus (known as Covid-19 pandemic), numerous studies were carried out to evaluate the role of pollution in the spread of the disease and its consequences on the severity of the effects caused and on mortality rates. This disease, similar to the severe acute respiratory syndrome (SARS) that occurred in 2002, broke out in Wuhan (China) in December 2019 and then spread worldwide. In Italy, the first cases of infection were officially reported at the end of February 2020, particularly in the northern regions. In March, a relationship was hypothesized between air pollution and the spread of SARS-Cov-2 infections. A position paper (Setti, Passarini, De Gennaro, Di Gilio et al., 2020) on this topic was published by some experts of the Società Italiana Medicina Ambientale (SIMA) together with researchers from Italian universities. The authors analysed the daily concentration of PM10 and the number of infections by Covid-19, for each province. They found a relationship between the exceedances of PM10 limit values recorded in the period February 10^{th} - February 29^{th} 2020 and the number of COVID-19 cases updated to March 3^{rd}, considering that the infection is diagnosed with a latency time of 14 days. One month after the publication of the position paper, SIMA claimed to have ascertained the presence of the new coronavirus in particulate matter from the extraction of SARS-Cov-2 RNA (Setti, Passarini, De Gennaro, Barbieri et al., 2020). The analysis was carried out on 34 samples of PM10 collected for three weeks (from February 21^{th} to March 13^{th} 2020) in industrial sites located in the province of Bergamo. The results were confirmed on 12 samples for the three genes E, N, RdRP used as molecular markers. European Public Health Alliance (2020) stated that those who live in cities with high concentrations of pollutants are more exposed to the risks deriving from Covid-19. This hypothesis was made on the basis of statements made by the European Respiratory Society (ERS): people with chronic lung and heart diseases caused by long-term exposure to poor air quality are less able to fight lung infections and therefore also Covid-19. To confirm the hypothesis, results of a study conducted in 2003 on SARS (Cui et al., 2003) were also used. This study found that people living in regions with a moderate air pollution index present an 84% higher chance of death than inhabitants of regions with a low index. Research by Wu et al. (2020a, 2020b) showed that, in the long run, a difference of one microgram in the average of PM2.5 is sufficient to increase the mortality rate of Covid-19 by 11%. The analysis compares the levels of particulate matter recorded in 3089 American counties with deaths for Covid-19 until June 18th 2020 and examines several variables: population size, hospital beds, weather, socioeconomic and behavioural conditions. A study on Italian territory (Fattorini & Regoli, 2020) focused on the role of chronic exposure to air pollutants. From the analysis of NO2, PM2.5 and PM10 values detected in Italy in the last 4 years, it was found that Northern Italy has been constantly exposed to high levels of atmospheric pollution and there is a correlation between these data and the Covid-19 cases for 71 provinces.

In order to assess the level of atmospheric pollution and take action to ensure good air quality, limiting the spread of Covid-19 and other diseases, we intend to define the design of an urban monitoring system for air quality in smart cities of a size similar to that of the case study. The method takes into account the main anthropogenic sources of air pollution and it is applied in the smart city on the basis of the specific urban characteristics of the place under study and with the involvement of citizen science, creating a participatory process.

2 LITERATURE REVIEW

Collecting air quality data through monitoring networks allows to assess pollution levels and, where appropriate, suggests actions that are to be taken in order to avoid the adverse effects of pollution on the environment and human health (Kainuma et al., 1990). The chosen measurement points must ensure the best possible representativeness of the area's air quality and also take into account the location of point sources such as industrial sites (Kibble & Harrison, 2005). Hacıoğlu et al. (2020) pinpointed the locations of two air quality monitoring stations among potential urban and rural sites by using two techniques: Analytic Hierarchy Process (AHP) and Elimination Et Choix Traduisant la Realité III (ELECTRE III). This was done on the basis of seven criteria: pollution levels, security, availability of electricity, collaborations, staff support, easy access, distance. Both methods have identified the same positions, thus validating each other. Mofarrah et al. (2011) divided the study area into a grid where each square represented a possible position for the air quality monitoring network sensor. With the criteria of air quality, location sensitivity, cost, population sensitivity and population density, a fuzzy matrix of pairwise comparisons was formed and a score was assigned to each potential position. The optimal positions for the sensors were identified through the values obtained from the Fuzzy Analytical Hierarchy Process (FAHP) plus the degree of representativeness of the area. FAHP method was also used to evaluate the atmospheric environmental quality in five cities in China (Lv & Ji, 2019), achieving better results with an index system than the standard air pollution index.

A mathematical model that can be used to describe and simulate environmental phenomena varying in time and space is the cellular automaton. Benjavanich et al. (2017) modelled and simulated the flow of pollution with cellular automaton in an area of 3x3 km. A variable number of sensors was considered, and each cell was provided with updated levels of pollution and wind action. Marín et al. (2020) used cellular automata to simulate the spread of air pollution considering gravity, diffusion and wind transport as calibration factors. Lauret et al. (2016) combined cellular automata with artificial neural networks to evaluate the atmospheric dispersion of methane in 2D. In particular, the neural networks were used for making predictions and cellular automata for space-time simulation.

3 CASE STUDY

The case study of this research is the town of Santa Maria degli Angeli (43°03′32″N 12°34′41″E), a part of the Municipality of Assisi (Italy) with 8470 inhabitants. It is one of the main tourist destinations in the region, due to the presence of important religious sites. Over the years, the area has experienced an important urban development, becoming equipped with all the services necessary for residential settlement and, in addition, also with industrial activities, favoured by the presence of the railway line and the proximity to the highway. These industrial activities are mainly concentrated in the south-west area, but there is also a foundry near the inhabited centre. Together with the road traffic, which concentrates on the three main axes of connection with important road arteries and with the nearby urban centers, these activities are the main sources of pollution for the town (Figure 1).

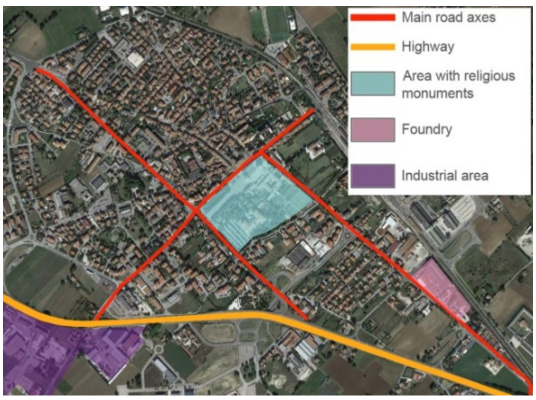

Figure 1: View of study area.

4 METHODOLOGY

Based on the studies in the literature and the importance of air pollution assessment in order to safeguard the health of citizens, we want to propose a design method for a low-cost urban monitoring system of air quality that can be implemented in any small-to-medium-sized smart city. In particular, we propose to create a LoRaWAN network, with the location of the sensors determined through the application of the Analytic Hierarchy Process (AHP) multi-criteria decision-making technique between many potential positions and optimized through the application of the mathematical model of cellular automata in order to ensure the best overall coverage of the polluted area. For the case study, the configuration of the LoRaWAN network, which consist of six sensors, is initially established among twelve alternatives by use of the AHP method. These positions are corrected using cellular automata, assigning a transition probability determined by the level of pollution present in the neighbourhood of the sensor. The sensors will detect the amount of PM10 and PM2.5 which, as discussed in the introduction, have been showed to play a key role in the spread of viruses.

4.1 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a multi-criteria decision-making technique, developed by Thomas Lorie Saaty in the 1970s, which allows to assign priorities to a series of decision-making alternatives and define them on a single scale, relating parameters that are not directly comparable, such as qualitative and quantitative evaluations. The method is applied in three steps: definition of a hierarchy of the problem, comparison of judgments and calculation of the priority vector, hierarchical recomposition (*Analytic Hierarchy Process*, n.d.). As regards the hierarchy, the final objective is placed at the highest level, then come the various criteria that contribute to the objective and finally the different alternatives to be evaluated. In the second phase, in order to evaluate how much each criterion affects the final decision, a pairwise comparison matrix is constructed by assigning the judgments according to the values of the fundamental scale (Table 1). The matrix is square and of size equal to the number of elements of the hierarchical level being considered. For n criteria, with $i, j = 1,2,..n$, the matrix of pairwise comparisons is:

$$A = \{a_{ij}\} \tag{1}$$

where a_{ij} indicates how much the i-th criterion is more important than the j-th. If $a_{ij} > 1$, the element i is preferred to j; if $a_{ij} < 1$, the opposite is true. In order to make consistent judgments, it must be established that:

- $a_{ji} = 1/a_{ij}$ for $i, j = 1,2,..n$.
- $a_{ik} = \sum_{j=1}^{n} a_{ij} \cdot a_{jk}$ for all $i, k = 1,2,..n$.

The same type of pairwise comparison is carried out among the alternatives referred to each criteria.

For each matrix considered, the priority vector is obtained from the components of the main eigenvector w corresponding to the main eigenvalue λ_{max} of the matrix A:

$$A \cdot w = \lambda_{max} \cdot w \tag{2}$$

At this point, the consistency of the assessment is verified by calculating the Consistency Index ($C.I.$):

$$C.I. = \frac{\lambda_{max} - n}{\mathrm{n} - 1} \tag{3}$$

if this is less than 10% of the Random Inconsistency ($R.I.$) value for the corresponding is

Table 1: The fundamental scale for pairwise comparison.

Intensity of importance	Definition
1	Equal importance
2	Weak importance
3	Moderate importance
4	Moderate plus importance
5	Strong importance
6	Strong plus importance
7	Very strong importance
8	Very, very strong importance
9	Extreme importance

Table 2: Values of Random Inconsistency ($R.I.$).

n	$R.I.$	n	$R.I.$
1	0.00	6	1.24
2	0.00	7	1.32
3	0.58	8	1.41
4	0.90	9	1.45
5	1.12	10	1.49

number of elements n (Table 2), the decision acceptable (*Analytic Hierarchy Process (AHP)*, n.d.). Otherwise, the reasons for the inconsistency should be analysed and the judgments reviewed in order to reduce the inconsistency. In the last phase, the global weights of the alternatives are defined by applying the principle of hierarchical composition, determining their order of importance: the local (i.e. within a given level) weights of each alternative are multiplied by those of the corresponding higher-order criteria and the products thus obtained are added together (Latora et al., 2018).

4.2 Cellular Automata

The concept of cellular automaton was introduced by J. von Neumann in 1947 and then applied in practice by J.H. Conway in "Game of life" in 1968. A cellular automaton is a discrete dynamic system: in such model space, time and properties of the automata can only assume a finite and countable number of states. It consists of a set of elements, called cells, organized in a regular spatial grid and taking on a finite number of states. The state of each cell at a certain moment evolves according to a given transition rule, with the updated state of a cell depending on the previous state of the cell itself and the states of the neighbourhood. The latter can be of various kinds, with most common examples including the von Neumann, Moore and Margolus neighbourhoods ((D'Ambrosio, 2003).

5 RESULTS

The application of the AHP method has made possible to identify the initial configuration of the sensor network for urban monitoring of air quality. In defining the AHP hierarchy, the final objective was placed at the top level, i.e. the identification of the most significant points for the monitoring activity, then the various criteria that contribute to the objective and therefore determine atmospheric pollution: home heating, traffic and presence of industrial activities. Potential sensor positions were located at the lowest level of the hierarchy (Figure 2). For the case study, these are twelve and were chosen in barycentric points of each urban sector (A-L) identified by the three main roads axes and the roads of major importance that lead into them (Figure 3). Generally, the composition of the matrices, then the attribution of judgments, and the resulting final output are determined by a single individual or a group decision. In this case, a mixed approach was used: a participatory process, with the direct involvement of citizens through questionnaires, was used to determine the hierarchy of the criteria and a more objective method, with a single judgment, to evaluate the different sensor positioning alternatives.

In the distributed questionnaire it was asked to express which is believed to be the main source of atmospheric pollution among home heating, traffic and the presence of industrial activities. In addition, it was asked how much the indicated source of pollution was more decisive than the other two, expressing a value in the scale from 1 to 9. The anonymous questionnaires were distributed to a heterogeneous sample of citizens, inhabitants of the study area, of different ages and gender. 38 questionnaires were collected, mostly from people over the age of 60, 19 males and 19 females, who have been living in that area for more than 10 years and spend the whole day there. Of 38 questionnaire replies, 25 indicated industrial activities as the main source of pollution, 13 indicated traffic and 0 home heating. Given the values with which they expressed the importance of the main source of pollution compared to the other two, the geometric mean was calculated and approximated to the nearest integer number in order to compose the matrix of pairwise comparisons. In particular, it was obtained that the presence of industrial activities has a very, very strong importance (value 8) compared to home heating and strong importance (value 5) compared to traffic; instead, traffic has a very strong importance (value 7) compared to home heating. The same matrix is composed of the values 1 in the main diagonal, because it concerns the pairwise comparison of an element with itself, and of the reciprocal values of those already indicated, disallowing inconsistent judgments (Table 3). The eigenvector of the matrix was calculated and the weight of each criterion was found: 0.0544 for home heating, 0.2331 for traffic and 0.7125 for industrial activities. The Consistency Index ($C.I.$) is equal to 0.12 and therefore higher than 10% of the Random Inconsistency ($R.I.$) value for three elements. Being

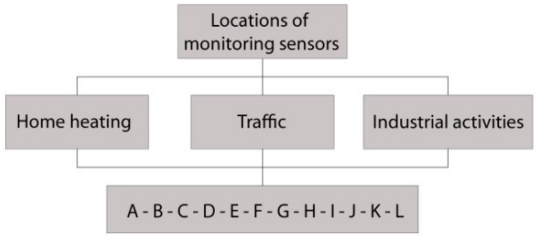

Figure 2: AHP hierarchy for the selection of sensor positions for the case study.

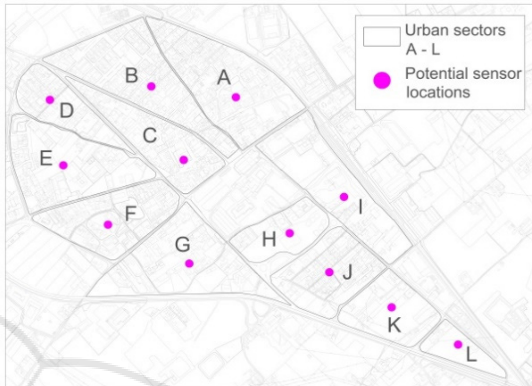

Figure 3: Potential positions of the air quality monitoring sensors in the study area.

a value deriving from a group decision and having used the geometric mean, it was still considered acceptable, without going to review the judgments. In fact, in the case of group decisions, three conditions must be verified: symmetry, linear homogeneity and concordance: the use of the geometric mean allows to respect all three and also to have reciprocity and separability (*Analytic Hierarchy Process*, n.d.). The evaluation of the twelve alternatives for the home heating criterion was made on the basis of the population data in each sector, recorded in the Municipality database. A higher population corresponds to a higher use of home heating. Sector B has the highest number of inhabitants while sector L has the lowest one. The population of each sector was compared with that of the others and the pairwise comparisons were made objectively, assigning the values in the fundamental scale. Regarding the traffic criterion, the analysis was carried out considering how each sector is enclosed by very busy roads, therefore by the connecting axes with the nearby urban centres and by the highway. The values associated with each sector were compared in pairs and the matrix was again formed using the fundamental scale of the AHP. The evaluation of each of the twelve alternatives with regard to the criterion of the

Table 3: Matrix of pairwise comparisons of the criteria.

	Home heating	Traffic	Industrial activities
Home heating	1	1/7	1/8
Traffic	7	1	1/5
Industrial activities	8	5	1

presence of industrial activities was made considering the average distance of each sector from the foundry and the industrial area to the south-west of the town. Similarly to the two previous criteria, the values to include in the matrix were identified in a very objective way. The eigenvector of each matrix was calculated and the weights of each alternative relating to each criterion were obtained with the subsequent normalization. All the matrices were found to be consistent, having obtained in the order the following Consistency Indices ($C.I.$): 0.1071, 0.099 and 0.1028, all less than 10% of the Random Inconsistency ($R.I.$) value.

Finally, the last step of the AHP method was carried out, namely the hierarchical recomposition, adding for each of the twelve alternatives the products of the local weights and the weights of the relative criteria (Table 4). The six alternatives to which correspond the highest global weights, that is, F, G, H, J, K and L, identify the initial configuration of the LoRaWAN network.

In this work, cellular automata are used to establish the final positions of the air quality monitoring sensors, optimizing the configuration obtained with the AHP method with the aim of maximizing the coverage of polluted areas. Firstly, the dimensions of the grid cells to superimpose on the study area were established. They were defined to be 200x200 m, thus obtaining an 11x8 grid. Twofold information was assigned to each cell: one variable takes into account the presence or absence of a sensor in the cell under scrutiny, and another one is related to the level of pollution. More in detail, the first variable was determined from the results of the AHP method, and the second derives from the answers of citizens to the questionnaires. This information forms the initial state of the cellular automaton (Figure 4). The transition rules guiding the system's dynamics are defined using Moore's neighbourhood, which is made of eight cells plus the starting one. At a given step during the system evolution, the configuration determines the set of positions of the sensors in the grid. At each iteration the sensor can move to one of the eight surrounding cells or remain in its current position.

Table 4: Results of AHP for the localization of monitoring sensors.

Sector	Home heating (0.0544)	Traffic (0.2331)	Industrial activities (0.7125)	Global weights
A	0.171	0.0214	0.0141	0.0244
B	0.3174	0.0149	0.0114	0.0288
C	0.1315	0.0546	0.0434	0.0508
D	0.0364	0.0434	0.0114	0.0202
E	0.0251	0.0159	0.0411	0.0344
F	0.08	0.0346	0.129	0.1043
G	0.1034	0.2832	0.2008	0.2147
H	0.0156	0.0271	0.1515	0.1151
I	0.0482	0.0546	0.0674	0.0634
J	0.0431	0.0689	0.2008	0.1614
K	0.0156	0.1685	0.1017	0.1126
L	0.0127	0.2128	0.0275	0.0698

The displacement of each sensor is determined stochastically according to the following procedure:

1) The coefficient k of polluted areas coverage is calculated for the current location of the sensor and for the other future possible positions, that is, the eight cells in its neighborhood. Given a certain cell, the k coefficient is defined as the weighted sum of polluted cells within the Moore neighborhood of the cell under consideration; the weights are chosen to decrease exponentially with the distance from the central cell in which the sensor is located. The matrix of weights is therefore the following:

$$\begin{bmatrix} 0.24 & 0.37 & 0.24 \\ 0.37 & 1 & 0.37 \\ 0.24 & 0.37 & 0.24 \end{bmatrix} \tag{4}$$

2) A probability p_i is assigned to each possible displacement on the basis of the calculated coefficients:

$$p_i = \frac{e^{k_i}}{\sum_i e^{k_i}} \tag{5}$$

3) The future position of the sensor is determined by random extraction among the nine possibilities, according to the probabilities p_i.

The new sensor configuration of is then compared with the previous one in order to assess whether it determines a greater overall coverage of polluted areas. The overall coverage is computed as the sum of the k_i coefficients of all sensors, also adding negative penalties if pairs of sensors lie in adjacent cells or in the same cell. The new configuration is accepted if it results in an increase of global coverage, otherwise it is discarded and the system remains in the previous configuration. According to this rule, the positions of the sensors in the case study were changed compared to the initial state and the configuration shown in Figure 4 was determined, ensuring a wider coverage of the polluted area.

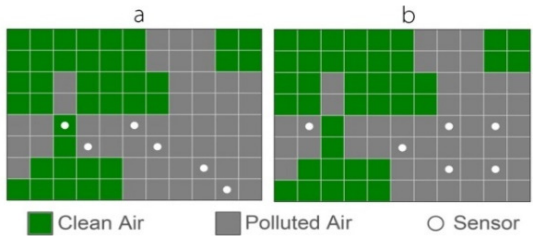

Figure 4: Evolution of sensor positions from the initial state (a) to the final configuration (b) through the cellular automaton.

6 CONCLUSIONS

This study focuses on the definition of a design method for an air quality urban monitoring system, useful for assessing pollution levels which derive from different sources. The method allows to identify the most significant positions for monitoring within the study area. Due to the nature of the problem, which required to evaluate different alternatives and to take into account more criteria, we applied the AHP multi-criteria decision-making technique. Citizens were involved in the decision-making through questionnaires, where they were asked to fill in the pairwise comparison matrix of the criteria. The group decision has identified the following scale of criteria: industrial activities (0.7125), traffic (0.2331) and home heating (0.0544). The twelve sensor position alternatives were evaluated with regard to the three criteria, in an objective way and with a single judgment, considering the specific features of each sector: number of inhabitants, exposure to very busy roads and average distance from industrial activities. The hierarchical recomposition produced the global weights and determined the order of preference of the alternatives. The first six sectors, namely sectors F, G, H, J, K and L, are the one where the six LoRaWAN sensors for urban monitoring of atmospheric particulate matter (PM10 and PM2.5) should be placed. However, in order to maximize global coverage of polluted areas, an optimization of the mentioned AHP configuration was carried out using a cellular automaton. After defining the grid and the type of neighbourhood, a procedure was devised, allowing the evolution of the state (presence/absence of sensor) of the cells based on a transition probability determined as a function of coverage coefficients k of the cells in the neighbourhood. Using this model, the positions of the sensors that had been found with the AHP method were corrected to achieve greater coverage of the polluted area, thus establishing the final configuration of the network.

The future development of this work will deal with a more refined optimization of the sensors positioning, considering levels of pollution determined not only by the replies to the questionnaires but also by the data actually detected by the sensors and, importantly, the epidemiological data regarding respiratory and cardiovascular diseases associated with long-term exposure to high levels of pollution. Therefore, when the sensors will be installed in the final configuration determined in the present study, and when a significant amount of measurements of pollutants detected by those sensors will have been collected, the cellular automaton will be run again. It is important to stress that the method to define an urban air quality monitoring system proposed in this study lends itself to be implemented in other smart cities, with variable numbers of sensors and the possibility of taking into account more pollutants.

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REFERENCES

Ambient (outdoor) air pollution. (2018, May 2). World Health Organization. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

Analytic Hierarchy Process. (n.d.). Università degli Studi di Napoli. Retrieved September 15, 2020, from https://www.docenti.unina.it/webdocenti-be/allegati/materiale-didattico/557402

Analytic Hierarchy Process (AHP). (n.d.). Università Ca' Foscari Venezia. Retrieved September 15, 2020, from http://virgo.unive.it/paolop/papers/appunti_ahp.pdf

Benjavanich, S., Ursani, Z., & Corne, D. (2017, December). Forecasting the flow of urban pollution with cellular automata. In *2017 Sustainable Internet and ICT for Sustainability (SustainIT)* (pp. 1-6). IEEE. 10.23919/SustainIT.2017.8379801

Chen, P. S., Tsai, F. T., Lin, C. K., Yang, C. Y., Chan, C. C., Young, C. Y., & Lee, C. H. (2010). Ambient influenza and avian influenza virus during dust storm days and background days. *Environmental health perspectives*, *118*(9), 1211-1216.

Cui, Y., Zhang, Z. F., Froines, J., Zhao, J., Wang, H., Yu, S. Z., & Detels, R. (2003). Air pollution and case fatality of SARS in the People's Republic of China: an ecologic study. *Environmental Health*, *2*(1), 1-5.

D'Ambrosio, D. (2003). *Automi Cellulari nella modellizzazione di fenomeni complessi macroscopici e loro ottimizzazione con Algoritmi Genetici*. Università degli Studi della Calabria. https://www.mat.unical.it/spataro/teaching/modelli/TesiPhD_Dambrosio.pdf

De Marco, A., Proietti, C., Anav, A., Ciancarella, L., D'Elia, I., Fares, S., Fornasier, M. F., Fusaro, L., Gualtieri, M., Manes, F., Marchetto, A., Mircea, M., Paoletti, E., Piersanti, A., Rogora, M., Salvati, L., Salvatori, E., Screpanti, A., Vialetto, G., Vitale, M., & Leonardi, C. (2019). Impacts of air pollution on human and ecosystem health, and implications for the National Emission Ceilings Directive: Insights from Italy. *Environment international*, *125*, 320-333.

De, S. (2020). Long-term ambient air pollution exposure and respiratory impedance in children: A cross-sectional study. *Respiratory Medicine*, *170*, 105795.

European Public Health Alliance. (2020, March 16). *Coronavirus threat greater for polluted cities*. EPHA. https://epha.org/coronavirus-threat-greater-for-polluted-cities/

Fattorini, D., & Regoli, F. (2020). Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. *Environmental Pollution*, 114732.

Ghorani-Azam, A., Riahi-Zanjani, B., & Balali-Mood, M. (2016). Effects of air pollution on human health and practical measures for prevention in Iran. *Journal of Research in Medical Sciences*, *21*(1), 65.

Hacıoğlu, H., Ari, A., Özkan, A., Elbir, T., Tuncel, S. G., Yay, O. D., & Gaga, E. O. (2016). A new approach for site selection of air quality monitoring stations: Multi-criteria decision-making. *Aerosol and Air Quality Research*, *16*(6), 1390–1402.

Kainuma, Y., Shiozawa, K., & Okamoto, S. I. (1990). Study of the optimal allocation of ambient air monitoring stations. *Atmospheric Environment. Part B. Urban Atmosphere*, *24*(3), 395-406.

Kibble, A., & Harrison, R. (2005). Point sources of air pollution. *Occupational Medicine*, *55*(6), 425-431.

Kurt, O. K., Zhang, J., & Pinkerton, K. E. (2016). Pulmonary health effects of air pollution. *Current opinion in pulmonary medicine*, *22*(2), 138.

Latora, A., Trapani, N., & Nicosia, G. (2018, July). Una metodologia di Multi Criteria Decision Making a supporto dei processi di Public Management. *Rivista italiana di Public Management, 1*(2). https://www.rivistaitalianadipublicmanagement.it/una-metodologia-di-multi-criteria-decision-making-a-supporto-dei-processi-di-public-management/

Lauret, P., Heymes, F., Aprin, L., & Johannet, A. (2016). Atmospheric dispersion modeling using Artificial Neural Network based cellular automata. *Environmental Modelling & Software*, *85*, 56–69.

Lv, W., & Ji, S. (2019). Atmospheric environmental quality assessment method based on analytic hierarchy process. *Discrete & Continuous Dynamical Systems - S*, *12*(4–5), 941–955.

Marín, M., Rauch, V., Rojas-Molina, A., López-Cajún, C. S., Herrera, A., & Castaño, V. M. (2000). Cellular automata simulation of dispersion of pollutants. *Computational Materials Science*, *18*(2), 132–140.

Mitchell, M., Gramss, I.T., Bornholdt, S., Gross, M., & Pellizzari, T. (2005). Computation in Cellular Automata: A Selected Review. *Non-standard Computation*.

Mofarrah, A., Husain, T., & Alharbi, B. H., (2011). Design of Urban Air Quality Monitoring Network: Fuzzy Based Multi-Criteria Decision Making Approach. *Air Quality Monitoring, Assessment and Management*, *11*, 25-39.

Samad, A., & Vogt, U. (2020). Investigation of urban air quality by performing mobile measurements using a bicycle (MOBAIR). *Urban Climate*, *33*, 100650.

Setti, L., Passarini, F., De Gennaro, G., Barbieri, P., Perrone, M. G., Borelli, M., Palmisani, J., Di Gilio, A., Torboli, V., Fontana, F., Clemente, L., Pallavicini, A., Ruscio, M., Piscitelli, P., & Miani, A. (2020). SARS-Cov-2RNA Found on Particulate Matter of Bergamo in Northern Italy: First Evidence. *Environmental Research*, 109754.

Setti, L., Passarini, F., De Gennaro, G., Di Gilio, A., Palmisani, J., Buono, P., Fornari, G., Perrone, M. G., Piazzalunga, A., Barbieri, P., Rizzo, E., & Miani, A. (2020). Position Paper Relazione circa l'effetto dell'inquinamento da particolato atmosferico e la diffusione di virus nella popolazione. SIMA-Società Italiana di Medicina Ambientale; 2020.

World Health Organization. (2006). *WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: global update 2005: summary of risk assessment*. https://apps.who.int/iris/bitstream/handle/10665/69477/WHO_SDE_PHE_OEH_06.02_eng.pdf

Wu, X., Nethery, R. C., Sabath, M. B., Braun, D., & Dominici, F. (2020a). Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. *Science Advances*, *6*(45), eabd4049.

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., & Dominici, F. (2020b). Exposure to air pollution and COVID-19 mortality in the United States. *medRxiv*.