Environ Monit Assess (2008) 136:87–99
DOI 10.1007/s10661-007-9725-z

# Multi-objective optimization of air quality monitoring

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Received: 1 January 2006 / Accepted: 19 December 2006 / Published online: 11 May 2007


**Abstract** A new method for multi-objective optimization of air quality monitoring systems based on satellite remote sensing of the troposphere is described in this work. The technique uses atmospheric turbidity as surrogate for air pollution loading. Through inverse chemical modeling and ancillary information the respective patterns of primary gaseous and particle pollutants are inferred. The optimization algorithm uses the resulting maps of ambient air pollution as input. It focuses on the gain of information with regard to human exposure to high pollution, potential impact on cultural heritage, compliance to ambient air quality standards, monitoring key point and area source emissions, as well as on the associated cost. Application of the method in Brescia, Italy showed its significant potential for improving the cost-effectiveness of air quality monitoring networks at the urban and regional scales.

**Keywords** Air quality monitoring · Air pollution index · Human exposure · Multi-objective optimization · Satellite Earth observation

## Introduction

Air pollution sampling site selection is one of the most important and yet most vexing of the problems faced by those responsible for regional and urban air quality management and for the attainment of National Ambient Air Quality Standards. The location, configuration and the number of stations are based on many factors, some of which may depend on limited resources, international, national and local regulations and local conditions. The combination of these conditions has made air quality surveys more complex, requiring comprehensive planning to ensure that the prescribed objectives can be met in the shortest possible time and at the least cost. Furthermore, the choice and location of the measuring network represents a factor of significant economic relevance for policy-makers. In view of the increasing costs of equipment, maintenance and operating personnel, optimization of monitoring design is a fundamental component for successful air quality management programs.

The design of a measurement network for air pollution monitoring involves both spatial and temporal sampling considerations. Most newly designed networks, however, use exclusively automatic continuous measuring equipment. These devices produce time-averaged values of pollutant concentrations measured over short intervals (on the order of a few seconds). As a consequence, these values can be considered as instantaneous for all practical purposes. This reduces the original spatial and temporal problem to one of space alone, i.e. the location of monitoring stations. The design and operation of air quality monitoring networks is determined by the objectives of the monitoring activities. The objectives of air pollution monitoring networks that have been reported in the relevant literature (US Environmental

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Protection Agency 1971; World Health Organization (WHO) 1977; Seinfeld 1972; Ott 1977) generally fall into one of the following categories.

1. Creation of databases containing current spatial–temporal air quality data in order to allow the analysis of long-term trends in air pollution or for research purposes such as the validation of mathematical models for air pollutant diffusion, transport and transformation.
2. Evaluation of the effectiveness of control strategies and activation of episode controls in highest pollution concentration areas ("trigger" function).
3. Evaluation of risks to human health with attention to densely populated areas.
4. Determination of the risk of damage to vulnerable receptors (e.g. historic and/or artistic valuable property, vegetation).
5. Development and updating of land-use planning databases.
6. Compliance with ambient air quality standards, i.e. detection of standard violations.
7. Control of emissions from singularly important sources, e.g. power plants or big industrial sites.

Generally implied within these objectives is also the minimization of the cost of the network. In addition to the above objectives, a series of regional regulations set the requirements on how monitoring and assessment of air pollution should be carried out. In the European Union, the present compound-specific Directives for $SO_2$ (89/427/EEC), $NO_2$ (85/203/EEC) and $O_3$ (92/72/EEC) issued during the period 1989–1995, require in principal that all exceedances of the limit values be detected. The Framework Directive on Ambient Air Quality (FWD) indicates that air quality is assessed relative to the limit values that are in effect at any time. Furthermore, the FWD requires that measurement of air quality is mandatory in agglomerations with population density higher than a certain value per $km^2$, which should be decided by the member states. Spatial coverage is another prerequisite for efficient air quality monitoring networks. All of the criteria should be taken into account for the design and establishment of a regulatory network aimed to report on compliance with the EU air quality directives.

At the same time, a new type of air quality monitoring network has been established in Europe. The European Topical Centre on Air Quality (ETC-AQ), under contract to the European Environment Agency (EEA) is required as part of its work program to develop and maintain a European Air Quality Monitoring Network. EUROAIRNET consists of a selection of monitoring stations from networks that are in operation in the European countries today. Its goals comprise the provision of a general description of air quality and its evolution over time, estimation of population as well as materials and ecosystem exposure, estimation of health effects, quantification of the damage to materials and vegetation, and support to legislation (Larseen et al. 1999).

Primary studies on optimization of Air Quality Monitoring Networks (herein referred as AQMN) have been primarily concerned with a few objectives of interest (Nakamori et al. 1979). But the recent literature shows a growing interest in addressing AQMN design as a multi-objective optimization problem. The incorporation of multiple objectives is considered as extremely important to lay the foundation of the future practices towards AQMN optimization (Munn 1981; Naioto and Ochiai 1981). As yet, however, only a few methodologies exist in the literature that can accomplish the task of designing a network capable of fulfilling all of the objectives stated above (Modak and Lohani 1984a, b; Trujillo-Ventura and Hugh Ellis 1991; Smith and Egan 1979). Every moderate or large scale multi-pollutant AQMN adheres to a policy of retaining a maximum number of common sites, i.e., sites where a number of pollutants are simultaneously measured. Networks with pollutant specific sites are rare. Economic and assessment considerations (Hickey et al. 1971; Hougland and Stephens 1976) appear to be the principal reasons for this. First of, economies of scale are significant, as the costs of installation and maintenance of the monitoring sites are shared amongst various pollutants, reducing, thus, greatly the total cost of monitoring. In many instances a common-site consideration is preferred for the following reasons:

1. Exposure assessment is never complete when only one pollutant is measured. It is well known that several pollutants have synergistic effects on health and therefore it is mandatory to measure certain pollutants at a common site.
2. If more than one pollutant is measured at a common site, then missing value estimation for a pollutant is possible especially when cross-correlations

between the other pollutants are quite high and already established.

Thus far there have only been limited attempts to produce optimal AQMN based on multiple pollutants. In fact, present multi-pollutant network optimization and design approaches focus on the combination of $SO_2$ with smoke (Modak and Lohani 1984a; Green 1966) due to their high degree of affinity. This is up to a certain point justifiable. Every pollutant has its characteristic variability due to its specific emission sources, rates of diffusion as well as transformations; and therefore it is quite logical that the optimal number and configuration are pollutant specific. As yet no references combining $O_3$, particulate matter, CO with $SO_2$ and $NO_2$ for the design of an AQMN have been cited in the literature. In the case of $O_3$ this could be due to the fact that this pollutant tends to have high values in the surroundings of a city and not in the city center. Thus high concentrations of $SO_2$ and $NO_2$ are actually associated with low values of $O_3$ and vice versa. The approach suggested herein, however, couples $NO_2$ and $SO_2$ as criteria pollutants for the AQMN design thanks to the aerosol model transformation. Pollution maps of $O_3$ and CO, created by kriging the available $O_3$ and CO concentration data measured from the present monitoring network, serve as an additional input in the methodology described below. At the same time, pollution maps of $SO_2$ and $NO_2$ based on a 4-year data series (1995–1998) were taken into consideration for the design of the recommended monitoring network. Since none of the available monitoring measures ultra-fine particles (PM2.5, PM1), literature references are used as guidelines for the integration of such particles into the optimal monitoring network (Kainuma and Shiozawa 1990). In this work, we develop an innovative methodology for multi-objective optimization of AQMNs, using both ground-based and satellite Earth observation-derived air pollution indicators. The proposed method was applied in the area of Brescia, in Lombardy, Northern Italy, a region that has been experiencing a significant increase in fine and ultra-fine particle incidents over the last decade.

## Methodology

Initially, we divide the area of interest in a $1\times1$ km grid. The intersections of the grid lines every 1 km are used as potential sites for ground-based air quality monitoring. The distinguishing feature of the method suggested in this work is the attempt to first identify the different classes of information, which can be derived from the operation of an AQMN with regard to their potential use and significance and then to synthesize them into a multi-objective utility function.

### Definition of optimisation objectives

#### *Representation of spatial–temporal patterns of pollution*

Conventional analytical air pollution observations produce time series of "space-deficient" point data, unless taken from an extremely large number of costly stations. Pollutant concentrations at any point in the domain have been, so far, estimated by interpolation from concentration data at locations where stations exist, through spatial correlation analysis and dispersion models. Earth observation from satellites, however, can offer spatial information on pollution, therefore reducing the uncertainties and errors associated with dispersion models (King et al. 1999).

Maps indicating the horizontal distribution of airborne particulate pollution can be produced by using high resolution satellite images produced from high spatial resolution (HSR) sensors aboard satellites (Sifakis and Deschamps 1992). Wavelength dependence of the optical effects of pollution allows the detection of even tenuous pollution, such as smoke wreaths from factories or diluted urban haze (Waggoner and Weiss 1980). It also allows the differentiation of pollution from natural clouds. The results of the present work have been based on a method developed within the frame of the European research project ICAROS (Sarigiannis et al. 2002). This method determines the nature and concentration of pollutants correlated with certain optical thickness values and is delineated below. Earth observation (EO) data provide direct information on atmospheric turbidity, as measured by the optical thickness of atmospheric aerosol. The profiles of aerosol optical thickness derived from EO refer to the total atmospheric column. It is reasonable to assume, however, that the majority of air pollutants of interest for air quality assessment remain within an atmospheric layer that spans from the ground till the tropospheric mixing layer height. Mixing height is calculated from meteorological data, based either on observation data or on meteorological models such as MM5. This information is then used to correct the optical thickness values derived from EO image processing (Fraser et al. 1984) and, thus, calculate the scattering coefficient of aerosol particles. This is based on the assumption that almost all tropospheric aerosol (both primary and secondary) affecting adversely human health is withheld within the well-mixed layer of the lower atmosphere. This is particularly true during convective meteorological conditions.

Air quality measurements from existing monitoring stations and measurement campaigns are stored in an air quality database. Ground data are used as input to chemical models used for the transformation of primary pollutants such as $NO_x$ and $SO_2$ into secondary aerosol. Although numerous chemical species have been identified in secondary aerosols, the most prevalent are sulphates, nitrates, ammonium and water. Therefore, the formation of secondary aerosol from gaseous $H_2SO_4$, $HNO_3$, $NH_3$ and $H_2O$ has been the subject of much theoretical and experimental investigation. Atmospheric gas–aerosol equilibrium models calculate the partitioning of total sulphate, nitrate, ammonium and water in an air parcel assuming that the system is in thermodynamic equilibrium (as expressed by its minimum Gibbs free energy). Knowledge of temperature, relative humidity and gaseous ammonia concentration is assumed. In most ambient situations, it is expected that equilibrium assumptions hold since the characteristic time for mass transfer to and from an aerosol particle is of the order of a fraction of a second (Saxena et al. 1986). By introducing the concentrations of these two acids, the ambient relative humidity and temperature in a thermodynamic equilibrium model, the mass and chemical composition of secondary inorganic atmospheric aerosols are estimated. Through this process and measurements of $PM_{10}$ and $PM_{2.5}$, the amount of atmospheric aerosol and the chemical species comprising it are calculated. Through a particle growth model, the aerosol particle scattering coefficient derived from satellite-based Earth observation and the ambient relative humidity are correlated to aerosol mass (derived from the calculation above) and the spatial pattern of aerosol in the area of interest can be estimated (Sarigiannis et al. 2004).

*Detection of violations over ambient standards*

Several objective functions have been used in the past to measure the ability of a network to detect violations of standards. The approach followed here measures the potential of a monitoring site to detect violations in terms of violation scores. In this way the semantic distance (the relative significance) of the various alternative solutions, i.e. the alternative station locations in terms of meeting the optimization objectives, is incorporated in the optimization algorithm. A location with a high violation score is considered to have a high potential for detection of violations. The computation of violation scores is essentially a weighted scoring of optical thickness values, which correspond to concentrations of priority pollutants above prescribed thresholds.

Several weighing functions have been reported including linear, segmented linear, non-linear, segmented non-linear etc. (Ott 1978). In this work, a segmented non-linear weighing function (Modak and Lohani 1984a, b, c) is used. The violation score for each candidate location is given by the equation,

$$V_i = \sum_{i=1}^{T} \sum_{k=1}^{N_t} \frac{(w_{k+1} - w_k)(x_i - x_k)X}{(x_{k+1} - x_k)} \qquad (1)$$

where

$V_i$ The violation score for the $i$th candidate location,
$w_k$ The weighing factor corresponding to threshold $x_k$,
$x_k$ The $k$th threshold,
$X$ $\begin{cases} 0, if\,(x_i - x_k) \leq 0 \\ 1, otherwise \end{cases}$
$N_t$ The total number of thresholds,
$T$ The total number of simulated observations,

The weighing function, associated with the violation scores, is important because the severity of threshold violations reported by two monitoring stations may differ.

In order to assist public authorities to manage and reduce health hazards and other risks of atmospheric pollution, the World Health Organisation, the European Commission, and national authorities publish guidelines and limit values for most of the common pollutants. Based on those guidelines, the values for thresholds for $SO_2$ and $NO_2$ were chosen as seen in Table 1.

The optical thickness ($\tau$) values that correspond (via the correlation analysis mentioned above) to

**Table 1** Air pollution index assigned to optical thickness values

| $NO_2$ (μg/m$^3$) | $SO_2$ (μg/m$^3$) | Threshold ($\tau$) | Weighing factor |
|---|---|---|---|
| 133 | 80 | 0.47 | 0.5 |
| 200 | 120 | 0.91 | 1.0 |
| 217 | 130 | 1.10 | 2.5 |
| 250 | 150 | 1.63 | 3.0 |
| 300 | 180 | 3.03 | 4.0 |

those values the air pollution index (weighing factor) ranging from 0 to 4 according to the severity of threshold exceedance are also listed. The exposure-response function underlying the assignment of the weighing factors is fitted to a binomial. This mathematical form penalizes non-linearly the exceedance of higher threshold values with regard to exceedance of lower ones, rendering thus network design consistent with the precautionary principle.

### *Risks to human health*

As several researchers have demonstrated (Lipfert 1994; Pope et al. 1995; Schwartz and Neas 2000; Brunekreef and Holgate 2002), particulate air pollution can be a good predictor of adverse effects on human health. The actual effects are, however, related to actual profiles of population exposure to airborne chemicals. Population exposure could only be assessed via detailed epidemiological studies and personal monitoring and not solely based on the data at fixed outdoor air quality monitoring stations. The EU-funded project EXPOLIS (Jantunen et al. 1998) was the first organized attempt to provide a large, population-based exposure study linked to air quality and associated health effects in Europe. In this and previous studies, substantial differences have been consistently found between the air pollution levels measured at the fixed outdoor monitors and levels to which people are actually exposed (Silverman et al. 1982; Jantunen et al. 1998). It may not be appropriate then to expect that a fixed outdoor AQMN, optimized for the maximization of population dosage product (Darby et al. 1974) would provide a rational basis for the assessment of health effects due to pollution. Such a network may only be considered as a cursory tool for placing the monitoring stations in the populated areas of probably higher relative concern.

### *Damage to cultural heritage*

Damage to cultural property in museums, libraries and historic buildings is caused by environmental pollution outdoors as well as indoors. Many attempts have been made in the past to provide some qualitative and quantitative characterization of the pollution profiles over building surfaces and inside them. As yet, no guidelines for the evaluation of exposure of historic and/or artistic valuable property to airborne chemicals have been established. Although many issues are now well-understood, additional research is needed to determine the susceptibility of materials with respect to composition, relative humidity and pollutants concentrations.

Thereafter, the area density of monuments expressed in number of cultural heritage sites per km$^2$ has been considered as an additional criterion for optimal location of an air pollution monitoring network. Site identification (in terms of exact geographic co-ordinates) of the most important cultural monuments in the area of study was not feasible. The only available information was the number of identified monuments per municipality in Lombardy, with no information on the type or the relative importance of the monument. Therefore, a normalized grading system was used, whereby the municipalities of Lombardy were sorted with regard to their relative importance as measured by the number of catalogued cultural monuments existing in their territory.

### *Reciprocal relationship between land-use and pollution*

Atmospheric pollutant emission inventories depend heavily on land use patterns. In turn, the state of air quality in a region influences over time the type of activities that prevail and, consequently, the spatial and temporal pattern of land use. A fixed ground-based monitoring network of air quality has to maintain its reliability and efficiency over time; the changing patterns of land use should, therefore, be taken into account when determining the spatial design of the network.

The land-use in Lombardy was taken from the EU land cover database, CORINE. Through these maps, information on the distribution of pollution sources and the land cover was derived. Land use categories were divided in three levels. In total, there are 44 land-use codes in the land use database. In the present study, we have considered 13 categories, listed in Table 2, as the most important ones for determining airborne toxicants emission patterns. A weight was assigned to each of them, according to the importance of placing a monitoring station in the grid-point that they represent.

*Note*: the importance weight of airports varies between 10 and 1, depending on the decision-makers' requirement to site a monitoring station in the vicinity of airport sites or not. Recent interest in the burden of airports on local air pollution and noise levels has made introducing this decision-making flexibility essential for optimized air quality monitoring.

*Minimum cost*

An important objective in the design of the network is the minimization of its total cost, or rather, the maximization of its cost-effectiveness. The economic assessment of an air monitoring station is primarily focused on determining the annual capital, maintenance/operation and replacement costs. Assuming that station installation and equipment will be financed with an annual rate of interest of $i$ and $n$ years of pay-off time, the annual installment for a station is given by:

$$A_{\mathrm{eq/year}} = C_{\mathrm{eq}}\left[\frac{i(1+i)^n}{(1+i)^n-1}\right] \tag{2}$$

where

$C_{\mathrm{eq}}$ Total installation cost for a new station
$C_{\mathrm{eq}}$ Cost of atmospheric pollutant monitors for a fixed station
$i$ Annual rate of loan interest
$n$ Years for paying off the loan

The *capital recovery coefficient*, $\left[\frac{i\times(1+i)^n}{(1+i)^n}-1\right]$, is used for the estimation of loan pay-off.

Assuming an increase in operational cost of $j$ every year due to inflation, the annual cost for O/M, both for a present station and a new station, is estimated by the equation:

$$A_{\mathrm{op/year}} = C_{\mathrm{op}}\left[\frac{(1+j)\left[(1+j)^T-1\right]}{T\times j}\right] \tag{3}$$

where

$C_{\mathrm{op}}$ Total operation and maintenance cost
$j$ Annual increase in operational cost
$T$ Lifetime of project, in years

For the purposes of this application, the lifetime of the project was assumed to be 20 years.

It is assumed that the useful life of the automatic analyzers for primary gases is 5 years; thus the analyzers have to be replaced every 5 years. The annual cost for the replacement of analyzers, assuming also an annual increase of $j$ in the cost of automatic analyzers is given by the equation:

$$A_{\mathrm{rep/year}} = C_{\mathrm{monitors}}\frac{(1+j)^5+(1+j)^{10}+(1+j)^{15}}{T} \tag{4}$$

**Table 2** CORINE land cover nomenclature and respective importance weights

| Level 1 | Level 2 | Level 3 | Weight |
|---|---|---|---|
| 1. Artificial surfaces | 1.2. Industrial, commercial and transport units | 1.2.1 Industrial or commercial units | 0.4 |
| | | 1.2.4 Airports | 10 or 1 |
| | 1.4. Artificial non-agricultural vegetated areas | 1.4.1 Green urban areas | 0.25 |
| | | 1.4.2. Sport and leisure facilities | 0.25 |
| 2. Agricultural areas | 2.1. Arable land | 1.1.1. Non-irrigated arable land | 0.3 |
| | | 1.1.2. Permanently irrigated land | 0.3 |
| | | 1.1.3. Rice fields | 0.3 |
| | 2.2. Permanent crops | 2.2.1. Vineyards | 0.3 |
| | | 2.2.3. Olive groves | 0.3 |
| 3. Forests and semi-natural areas | 3.1. Forests | 1.1.1. Broad-leaved forest | 0.2 |
| | | 1.1.2. Coniferous forest | 0.2 |
| | | 1.1.3. Mixed forest | 0.2 |
| 4. Wetlands | 4.1. Inland wetlands | 4.1.1. Inland marshes | 0.2 |

The total annual cost for one monitoring station is given by the sum of

$$C = A_{\mathrm{eq/year}} + A_{\mathrm{op/year}} + A_{\mathrm{rep/year}} \tag{5}$$

Information function approach

This approach is based on the establishment of an information function (IF) that encompasses the multiple objectives of network design.

$$\mathrm{IF} = \frac{(V \times P) + L + M}{C} \tag{6}$$

where

$V$ Violation score
$L$ Land-use score
$M$ Density of cultural heritage sites
$P$ Population density
$C$ Cost function

The variables above are calculated separately for each grid-point in the area of interest, which is treated as a candidate location for the placement of a monitoring station.

Note that we use the Population Dosage Product ($V \times P$, herein referred to as PDP) to assign a premium to the monitoring sites with a lot of relevance for exposure assessment. This would imply that if a location had a high violation score but zero human population density, then the only information gained by placing a station at the respective location would

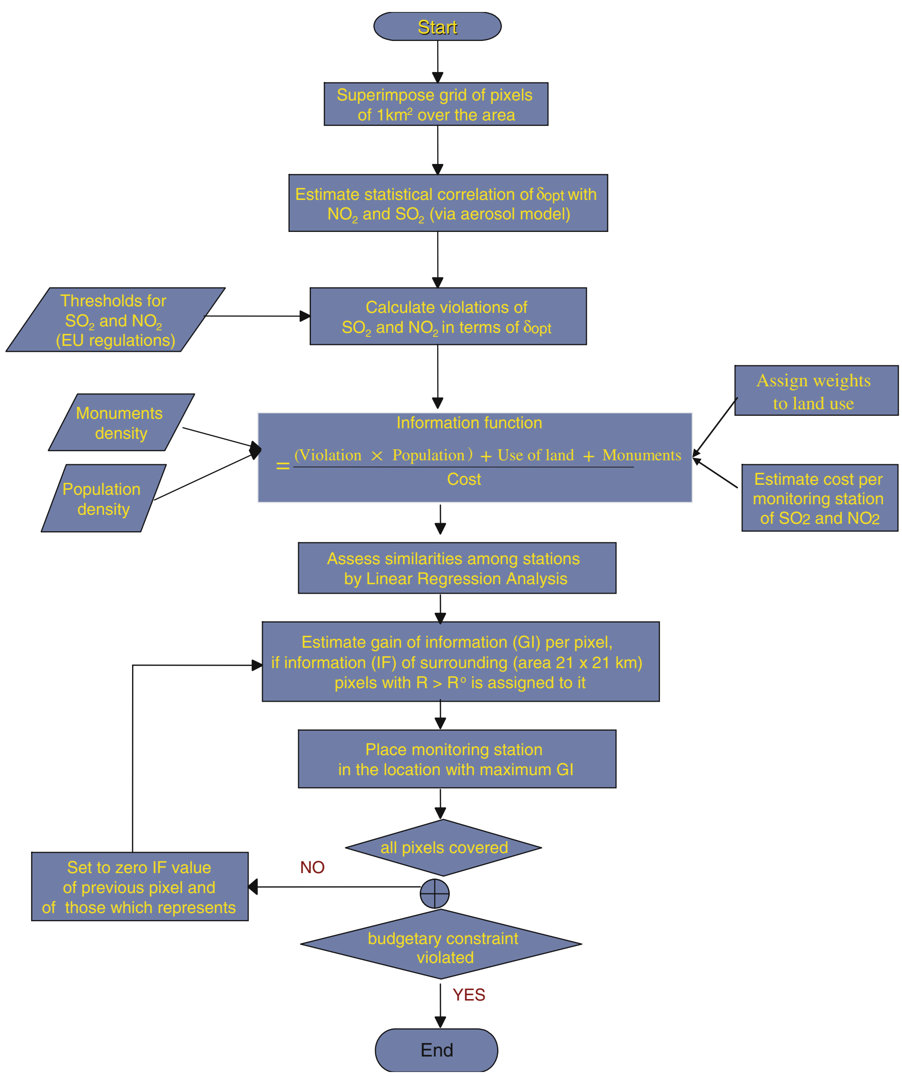


**Fig. 1** Information flow-chart of the multi-objective optimization of networks algorithm

be associated with the type of land-use and the density of the monuments. Each location reports a certain amount of information. Since the domain shows various degrees of dependence between locations, the information gain from such dependencies must be taken into consideration for the optimization of the air quality monitoring network. Linear regression analysis (LRA) can be used to analyze dependencies or overlaps among stations. Similarities among locations are assessed via the linear correlation coefficient between locations. If the correlation coefficient $R$, between two locations is higher than a cut-off value $R^0$, then the locations are considered to be dependent. The optimization problem is therefore transformed into the identification of the optimum number and configuration of monitoring stations, in order to obtain the maximum gain of information in the area of interest with the minimum possible overlap between stations.

A linear correlation matrix of $n \times n$ values of the correlation coefficients between the pollution index values of the central grid-point and the surrounding $n-1$ ones is constructed for each grid-point. For $R$ higher than $R^0$, the gain of information (**GI**) is given by the equation:

$$\mathrm{GI}_i = \sum_{k=1}^{n^2} R_{ik} \times \mathrm{IF}_i, \text{ if } R_{ik} \geq R^0 \tag{7}$$

where

$i$ $i$th location of a grid-point in the large grid
$k$ $k$th location of a grid point in the small $n \times n$ grid of cells

The information reported by the dependent grid-points is attributed to the central grid-point. The location with the maximum value of GI is selected as the best monitoring location. The information of those grid-points that are represented by the first monitoring location as well as the information of the first best monitoring location is set to null for the calculations to follow. In this way minimum overlap between the first and the following monitoring location is achieved. The GI matrix is recalculated and the location with the highest value of GI is identified. This is selected as the next best monitoring station. The values of information of the second monitoring station and of the grid-points represented by it are again set to null and the GI matrix is calculated anew. This procedure of sequential selection of monitoring sites is repeated until all the grid-points in the region are completely covered or the budgetary constraint is violated. The flowchart of the MOON algorithm is given in Fig. 1.

## Results and discussion

The multi-objective optimization method outlined above was applied in the extended area of the province of Brescia in Lombardy, northern Italy. The goal was to determine the minimal set of monitoring stations that would allow representative coverage of air quality in the province and the hierarchization of the present monitoring stations in terms of delivery of air quality-relevant information as shown in Figs. 2 and 3.

The values of aerosol optical depth have been extracted by images obtained by high spatial resolu-

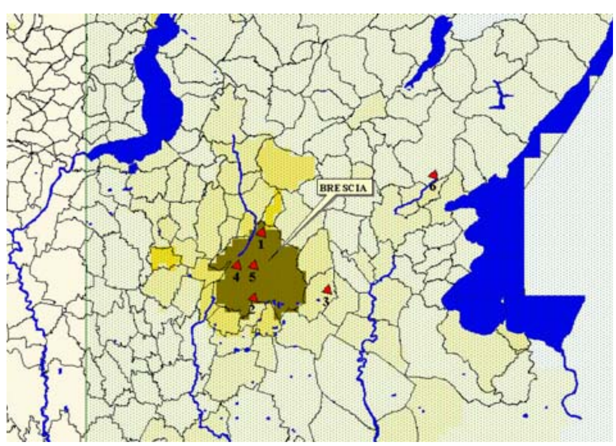


**Fig. 2** Configuration of six most important present stations in Brescia

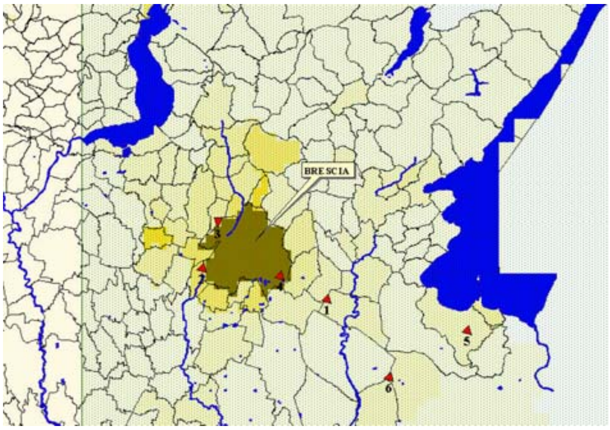


**Fig. 3** Configuration of optimally placed monitors in the Brescia. Cut-off value for $R^0$=0.85

tion (HSR) sensors on board in-polar-orbit Earth satellites (specifically SPOT 5 and Landsat 7) at the time of their daily overpass. Through an image processing algorithm (Sifakis et al. 1998) the spatial distribution of optical depth over the whole area is obtained. Assimilating the optical depth field with the field of the mixing layer height the scattering coefficient of lowermost part of tropospheric aerosol was reckoned. A physico-chemical and multi-phase thermodynamic equilibrium model was used to estimate the secondary aerosol formation and primary aerosol emission was estimated using the CORINAIR methodology for northern Italy. Using non-linear multiple regression the experiential relationship between the scattering coefficient of primary and secondary aerosol, its ambient air concentration and relative humidity was calculated (Sarigiannis et al. 2004). The physicochemical model that was found to best reflect the dependence of PM10 concentration on the ground with the scattering extinction coefficient and relative humidity is

$$C_{\mathrm{PM10}} = a \times \sigma_{\mathrm{e}} + b \times \mathrm{RH} \qquad \text{for RH} \leq \mathrm{RH_o} \tag{8}$$

$$C_{\mathrm{PM10}} = a' \times \sigma_{\mathrm{e}} + b' \times e^{K \times \mathrm{RH}} \qquad \text{for RH} > \mathrm{RH_o} \tag{9}$$

The exact value of the inflection point for RH, $\mathrm{RH_o}$, depends on the prevalent meteorological conditions (in terms of atmospheric humidity and ground-level air temperature). The factors $a$, $b$, $a'$ and $b'$ depend on the relative ratio of fine to coarse particles. $K$ is the kinetic constant of fine particle growth due to atmospheric humidity. The fraction of the variance explained by the square of the correlation coefficient is in the range of 70–73%, depending on season, type of land use, and ambient humidity range. From this spatially continuous field of concentration the values

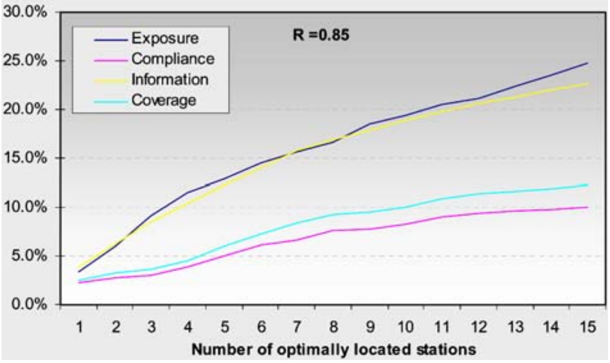


**Fig. 4** Relationship between number of monitors and the effectiveness of the optimally located stations in Brescia

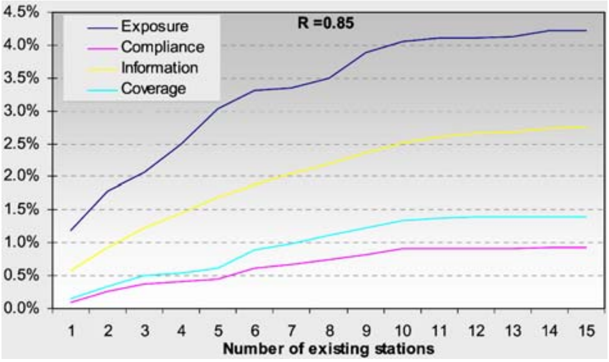


**Fig. 5** Relationship between number of monitors and the effectiveness of the existing stations in Brescia

that correspond to the sites of monitoring stations for which ground-based measurements of pollutants concentrations are available are extracted.

An extensive evaluation of the effectiveness of the optimized monitoring network was performed, based on five performance indicators:

1. *Percentage Exposure* defined as the ratio of PDP detected by the AQMN to that of total PDP calculated by summing over all the candidate locations.
2. *Percentage Compliance*, which denotes the ratio of the violation score detected by the AQMN to that of the total violation score calculated by summing over the violation scores at all candidate locations.
3. *Percentage Information*, which is the ratio of the information gained by the AQMN to the total information gain calculated by summing over all candidate locations.
4. *Percentage of Coverage*, which measures the ratio of the number of candidate locations covered by the AQMN, in terms of dependency of those locations to the total number of candidate locations. Location interdependency is estimated from linear regression analysis of the optical thickness values.
5. *Total Cost* of the AQMN.

These five indicators combine the objectives of both regulatory and EUROAIRNET networks regarding pollution in densely populated areas, detection of exceedances (or near exceedances), representative air quality information and coverage of large areas. $SO_2$ and $NO_2$ are selected as first priority indicators of exposure of all three important receptors of air pollution (population, materials and ecosystems) to be included in EUROAIRNET.

Application of the MOON algorithm results in a six-fold increase in the potential of the monitoring network to account for population exposure to pollution compared to the exposure reported by the current network in Brescia with 15 stations. Figures 4 and 5 illustrate the performance and the optimal configuration of the optimised network and of the present one respectively for a cut-off value of 0.85 for the monitor location interdependency coefficient.

It is noteworthy that six new stations optimally located would account for 14.5% of population exposure to pollution, which is an improvement by 200% relative to the exposure reported by the current network in Brescia with 15 stations. Even if the existing stations in are not optimally deployed, a smaller network of six of the existing stations would be sufficient to report the 78% of the exposure of the present network. The remaining nine present stations could be considered redundant for all practical purposes; they only provide information concerning the 12% of the current monitoring network. Table 3

**Table 3** A comparison between optimal and streamlined configuration of the stations in Brescia

| Type of network | | Number of stations | Cost ML | Percentage exposure | Percentage compliance | Percentage information | Percentage coverage |
|---|---|---|---|---|---|---|---|
| Optimal | $R$=0.85 | 6 | 632.0 | 14.5% | 6.2% | 14.0% | 7.2% |
| Present | $R$=0.85 | 15 | 1177.6 | 4.2% | 0.9% | 2.8% | 1.4% |
| Present streamlined | $R$=0.85 | 6 | 471.0 | 3.3% | 0.6% | 1.9% | 0.9% |

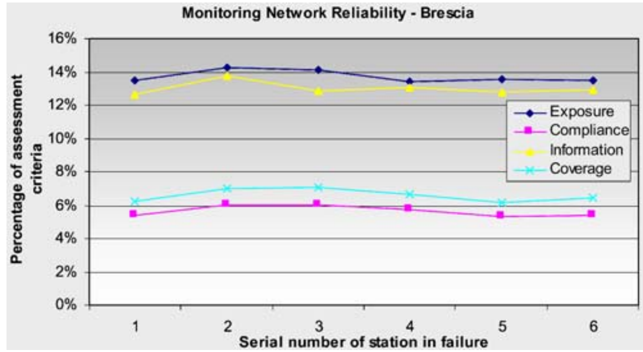


**Fig. 6** Reliability of optimal six-station network in the failure of one station at a time

summarizes the effectiveness of the optimal configuration and the reduced present network.

The reliability of the network in terms of being able to provide adequate air quality monitoring in the case of one station failure was tested. The four performance indicators of monitoring network performance have been reevaluated, under the assumption that one station fails to work properly and produce data. Reliability results are shown in Fig. 6 for the air quality monitoring networks in the city of Brescia. The cut-off correlation coefficient is 0.85 and no strong emphasis is placed on airports. The reliability of the optimal six-station network is also satisfactory. No significant changes can be seen due to the failure of any one station in the total amount of information or in the amount of exposure or compliance of the entire network.

For a stipulated budget, the air quality monitoring organization could maintain either a high or a low $R^0$-based network. A high $R^0$-based network may not necessarily cover the entire region, but the covered region will be well represented. A low $R^0$-based network on the other hand, would offer more coverage of the region, but the covered region may not be satisfactorily represented. The ultimate decision in such a case is left to the air quality monitoring authority. The marginal effectiveness of the monitoring network decreases as the monitors are sequentially selected, while the number of stations is subject to the budgetary constraint. A network designed for a higher value of $R^0$ is not necessarily a simple extension, i.e. a mere addition of monitors, as compared to that of the network obtained at a lower $R^0$ value. Expansion of a network to a higher reliability of representation, may not only require an additional number of monitors but perhaps also a relocation of existing ones as well. The combination of the type of information function (IF) used and the structure of this algorithm presents a rational method to calculate the best number of monitors in a region. Since this number explains the region-wide variance at a minimum overlap, any additional number of monitors would only result in redundancies as far as representation of the spatial–temporal pattern is concerned.

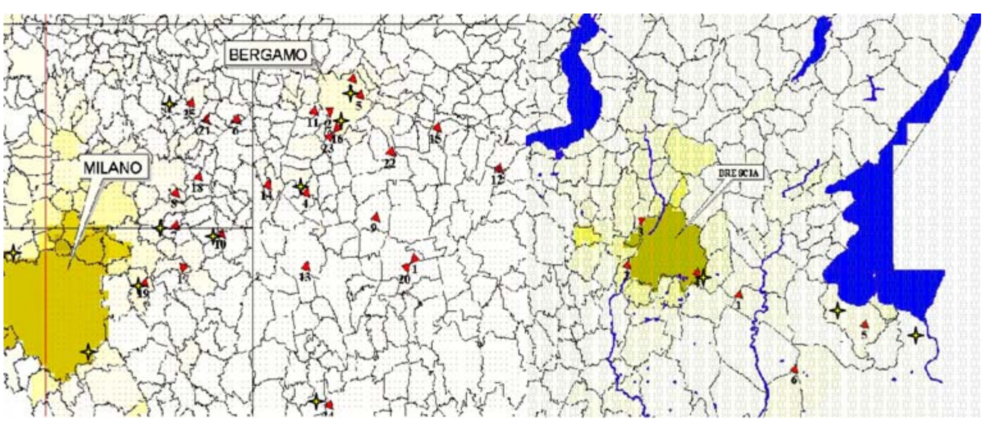


**Fig. 7** Comparison between optimal deployment of air quality monitors according to the MOON algorithm (*triangles*) and the positions of the most important monitors on the basis of historical time series analysis (*stars*) in Lombardy

A comparison between existing and optimum configurations shows that performance of the existing AQMN could be improved if the network design is based on rational considerations. In this case, for instance, a much lower number of carefully relocated monitors could lead to an improvement of the order of 100% in the effectiveness of the monitoring network, according to the summary of results given in Table 2.

The validity of the optimization scheme output has been validated on the basis of time series data from the existing ground monitoring network in the region of Lombardy, the administrative department encompassing the province of Brescia. The MOON algorithm was applied to the air quality monitoring network in Lombardy, focusing on the area between Milan, the capital, and the city of Brescia to the north-east. This is the main industrial and agricultural area of the region and it accounts for the largest part of atmospheric pollutants. The resulting configuration of the optimized air quality monitoring network coincided with the location of the most important monitoring stations (see Fig. 7). The most important stations were identified on the basis of statistical analysis of historical daily monitoring data over the last decade. As expected, the satellite-assisted optimal network identified the positions of the most important stations and added a few more monitors to meet the high spatial coverage and resilience requirements set by the regional administration competent for air quality control.

## Conclusions

The approach presented herein for determining the optimal configuration of new air quality monitoring networks and streamlining existing networks, is a significant addition to the tools available to those responsible for the design and operation of air quality monitoring networks. It provides monitor site assignments for primary gaseous pollutants such as $SO_2$ and $NO_2$, designed to maximize monitor coverage of a region as well as maximum gain of information, in terms of exposure of population, land-use and vulnerable cultural receptors at a minimum cost. At the same time, the optimal configuration of AQMN suggested herein follows the EU Directive on AQ monitoring and can provide EUROAIRNET with the most representative monitoring stations for the area of application. The method gives priority to areas with high emission levels without neglecting weaker sources. Finally, it is easy to use and inexpensive in computer resources. The second version of MOON is currently under development, with a view to incorporate ozone, carbon monoxide and coarse and fine particles into the list of pollutants considered as AQ indices. This will provide an integrated as well as unique method for designing monitoring networks in Europe, based on the EU Directive's most important pollutants, in terms of human health and vegetation protection.

**Acknowledgements** This work was partially supported financially by the European Commission under grants ENV4-CT97-0417 (ICAROS project) and IST-2000-29264 (ICAROS NET project) and by Regione Lombardia in the frame of the Regional Air Quality Plan (1998–2000). The authors wish to thank Dr Nicolas Sifakis for kindly providing horizontal maps of the aerosol optical depth field in the area.

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