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Optimization of sensor networks for the estimation of atmospheric pollutants sources

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Abstract

This study describes a process to design a sensor network. This network could include: wireless mobile sensors deployed by first responders in hazardous material operations, stationary sensors used to protect an area against accidental, or intentional, contaminations or stationary air quality monitoring stations. The objective of the network is the estimation (localization – quantification) of releases sources. The design of such a network has an important issue in determining the optimal placement of sensors. This paper presents the first application of the renormalized data assimilation method to address this issue. It is associated with a classical optimization algorithm (simulate annealing) to solve the combinatory optimization problem consisting of finding the optimal configuration of m sensors among a set of n potential positions. Three scenarios, corresponding with three different cost functions, are proposed. The first one consists of optimizing the design of a network deployed in emergency situations. Experimental data from a wind tunnel experiment are used. The objective is to characterize the source to minimize error in measurement forecasts. The second one is to optimize the design of the same network but in a situation where the source can be anywhere in the domain. To that end, an entropic criterion is used. The last one consists of optimizing the design of a stationary network. The objective is to characterize the source with varying meteorological conditions (experimental meteorological data are used).
Keywords: network optimization, source characterization, renormalized data assimilation.

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1 Introduction

In a defined geographical area, the concentrations in the air of hazardous gas can be measured by a network of sensors distributed over the area. In critical pollution situations, these near-live measurements can be transmitted to authorities, over high-speed data links, and used along with atmospheric dispersion models to provide the basics for decisions. Successful forecasts from dispersion models rely on an accurate and reliable estimation of the source strength and location. But an effective source determination from air concentration measurement strongly depends on the network design.

In recent years, several studies have examined the design of sensor networks for environmental process. They have dealt with: effective coverage [1], efficient monitoring [2], reconstitution of plume extent [3], detecting of species and threats presence [4]. Optimality criteria used in these studies were based either on the "Optimal Experimental Design" theory [5] or on the information theory [6]. Only few studies focus on optimal design for the pure purpose of source characterization. As an example Abida and Bocquet [7] presented a sequential reconstruction technique of dispersed plume by coupling inverse modelling to observation targeting strategy. This technique has been used to determine the optimal sensors' positions that improve the source term.

The aim of this study is to present a process to design sensor networks used to localize and quantify the sources of continuous pollutant released at local scale. This process, combines the renormalization inversion approach with classical optimization techniques. The proposed approach is a general framework within which more or less complex configurations can be studied. In the next section, the optimisation process is defined: the networks' objectives, the inversion technique and the optimization algorithm are presented. Then the process is evaluated versus experimental data for three scenarios (with mobile and stationary sensors at local scale).

2 The optimization process

2.1 Definition of the network objective

In view of the variety and plurality of goals [8], the objective of a network of $i = 1 \dots m$ sensors must be clearly identified. We mention, as examples the "detect to warn" objective (warn people before they receive toxic exposures) and the "detect to identify" objective (identify specific pollutants, to guide the medical response). In this study, the purpose is to design, optimally, a network of a predetermined number of detectors (a) to detect pollutant emissions (b) to localize and quantify their sources. This strategy could be named "detect to estimate". In critical situations, the purpose could be to provide estimates of the source strength and location to assess the extent of the plume and/or to forecast the plume evolution (with air pollution models). The purpose of the network could also be to generate atmospheric emission inventories by inverting the concentrations measured by air quality monitoring stations. The reconstruction of a pollutant source exploiting measured data after a monitoring network is an inverse problem. To address such a problem a specific method must be defined.

2.2 Choice of an inverse method

In this study, the deterministic renormalized data assimilation method, proposed by Issartel [9], is used. This approach exploits the linearity between the measured data and the source. In case of a continuous release, the source is described by a function $s(x,y)$ representing the rate of release of the pollutant per unit area and time at the location of horizontal coordinates x,y and altitude $z=0$ of the ground. The measurement μ_i sampled by the i^{th} detectors ($i = 1 \dots m$) can be written:

$$\mu_i = \int_\Omega s(x,y) a_i(x,y)\, dxdy \tag{1}$$

In which the adjoint function a_i gives the sensitivity of the i^{th} measurement with respect to emissions in the various regions of the ground Ω. This adjoint function is obtained by computing a dispersion model in a backward mode (i.e. by reversing the wind direction) and by considering the detector as a source with unit intensity [10]. In this study Gaussian dispersion model have been used.

The inverse problem consists of determining the source function $s(x,y)$ from a given vector of measurements $\boldsymbol{\mu}$. This problem is ill-posed and has an infinite number of solutions. In the renormalization method, only the component of the source parallel to the adjoint functions is considered [11]. Moreover, the adjoint functions are weighted by a function f in order to avoid singularities at sensors' locations. Equation (1) becomes

$$\mu_i = \int_\Omega s(x,y) \frac{a_i(x,y)}{f(x,y)} f(x,y)\, dxdy \tag{2}$$

The estimated source function is given by

$$s_f(x,y) = \boldsymbol{\mu}^{\boldsymbol{T}} \boldsymbol{H}_f^{-1} \frac{\boldsymbol{a}(x,y)}{f(x,y)} \tag{3}$$

where $\boldsymbol{a}(x,y)$ is the vector of the adjoint functions and $\boldsymbol{H}_f$ is the Gram matrix given by

$$H_{f_{ij}} = \int_\Omega \frac{a_i(x,y)}{f(x,y)} \frac{a_j(x,y)}{f(x,y)} f(x,y)\, dxdy \tag{4}$$

The choice of f should be as neutral as possible in order to minimize the information unduly introduced in the interpretation of the data (minimum entropy criterion). It has been shown by Busch [12] that this criterion corresponds to minimizing $\det(\boldsymbol{H}_f)$. The optimal function, that verifies this criterion is named the visibility φ and verifies the three following conditions:

$$(a)\ \varphi(x,y) > 0\ \ (b) \int_{\Omega} \varphi(x,y)dxdy = m\ \ (c)\ \frac{\boldsymbol{a}^{\boldsymbol{T}}(x,y)}{\varphi(x,y)} \boldsymbol{H}_{\varphi}^{-1} \frac{\boldsymbol{a}(x,y)}{\varphi(x,y)} = 1 \quad (5)$$

2.3 Problem statement

In this study, the region of interest Ω is a typical built-up suburban area with flat topography. The sensors network could include (i) wireless mobile sensors deployed by first responders in hazardous materials operations, (ii) stationary (fixed) sensors used to protect the area against accidental, or intentional, contaminations, (iii) stationary air quality monitoring stations deployed in the area to measure concentrations in the air of specific gas. In the region of interest, n potential locations are defined

$$P = \{(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)\} \subset \Omega \quad (6)$$

P can be either intuitively chosen or determined by a specific study. In case (ii), the potential locations should be in “danger zones” around the protected site. These zones can be identified from steady retroplumes scattered upwind from the site (figure 4(b)). Among these potential locations, we have to find the optimal configuration of m sensors

$$C^o = \left\{(x_1^o, y_1^o), (x_2^o, y_2^o) \dots (x_m^o, y_m^o)\right\} \subset P \quad (7)$$

2.4 Optimization algorithm

2.4.1 Definition of the cost function

To obtain C^o, a cost function must be defined in accordance with the purpose of the network. Following, three scenarios are proposed. Note that, in emergency situations (scenarios 1 and 2), one can often guess that the source has negligible extent relative to the spatial size of the domain of interest. In this case, it can be considered as a point source located at (x_s, y_s) and emitting a tracer with intensity $q_s > 0$. Moreover the actual meteorological conditions are known (real time measurements).

– *Scenario 1: The source has been roughly localized. The network is rapidly deployed on the site.* The objective is to obtain clear estimates of the source strength and location. The goal is to obtain reliable concentration forecasts from a dispersion model. The objective function to be minimized can be:

$$J_{S1} = \frac{1}{2}(\mu_{obs} - \mu_{mod})^T \boldsymbol{H}_{\varphi}^{-1}(\mu_{obs} - \mu_{mod}) = \|\mu_{obs} - \mu_{mod}\|^2{}_{\boldsymbol{H}_{\varphi}^{-1}} \quad (8)$$

where μ_{obs} and μ_{mod} are respectively the observed and modeled values of the concentrations.

– *Scenario 2: The source has not been yet localized. The network is rapidly deployed on the site.* The source can be anywhere in the domain. The optimal network must be efficient regardless of the source location. An entropic criterion, similar to the one proposed to define φ can be chosen. The objective function to be maximized can be defined as follows [12]:

$$J_{S2} = \frac{1}{2} log\big(det(\boldsymbol{H}_{\varphi})\big) \tag{9}$$

– Scenario 3: The network is permanent and fixed (to protect a site). One have no a priori knowledge of the source term (shape, localization etc...). The objective is to design an optimal network, which must be efficient irrespective of the meteorological conditions. These meteorological conditions (wind speed and directions) are statistically known. The objective function to be maximized can be:

$$J_{S3} = \sum_{i=1}^{k} \alpha_i \left\{ (log(\alpha_i) + \frac{1}{2} log\big(det(\boldsymbol{H}_{\varphi})\,\big) \right\} \tag{10}$$

where k is the number of wind direction considered and α_i is the wind frequency in direction i.

2.4.2 Choice of the algorithm

For all scenarios, the problem is essentially a combinatory optimization problem. As shown by Ko *et al.* [13] the problem of sensors network optimization is *NP-hard*. To solve such problems the Simulated Annealing (SA) algorithm is efficient. This algorithm designed for statistical physics, incorporates a probabilistic technique to explore the search space and converges iteratively to the optimum solution. The probabilistic treatment consists of accepting a new configuration with the probability (Metropolis rule):

$$p = \exp(\frac{\Delta J}{T}) \tag{11}$$

where ΔJ the cost difference between the previous and current configurations and T is a fictive temperature parameter which must be lowered gradually as the algorithm evolves. The cost associated with the accepted configuration is named the "best cost". The process begins by setting the initial and final fictive temperatures, T_0 and T_s, the temperature decrease scheme, the number of iterations for each temperature stage L_M and an initial configuration. Here, T_0 has been chosen as the pseudo temperature which correspond to the acceptance, with a probability of 0.8, of the mean cost difference $\overline{\Delta J}$ observed with a sample of 200 random configurations:

$$T_0 = \frac{-\overline{\Delta J}}{\log(0.8)} \tag{12}$$

The most simple and commonly used decay decrease scheme for T, i.e. the exponential cooling schedule, has been used:

$$T_{i+1} = \theta\, T_i \tag{13}$$

where θ is the decay factor such that $0 < \theta < 1$. The stopping criterion is reached when the temperature is equal to $T_s = r \times T_0$ where r is a fixed ratio.

3 Process evaluation

3.1 Evaluation for scenario 1

3.1.1 Experimental data

The optimal design process for scenario 1 (source roughly localized, network rapidly deployed) is evaluated with data from wind tunnel experiments conducted at the ENFLO (Environmental Flow Research Centre), Surrey University, United Kingdom [14]. During these experiments a gas mixture of 1.5% propane in air was released over a period of 15 min. The emission rate was 7.5×10^{-7} m^3s^{-1}. Four Fast Flame Ionization Detectors (FFID) were placed 10 mm above ground level. Eleven different configurations of the four sensors have been tested, corresponding with 27 potential positions (Figure 1).

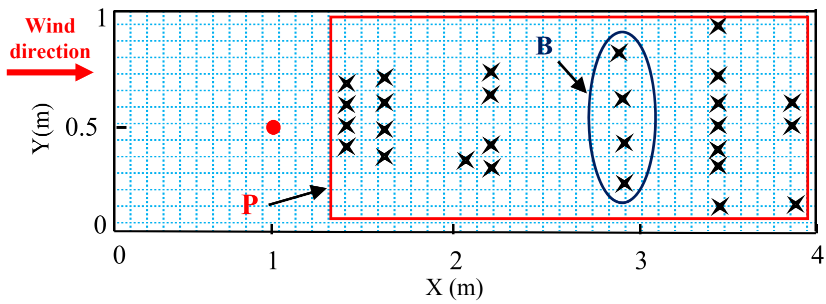

Figure 1: Schematic representation of the experiment, with the true source position (red circle), with the potentials positions (black stars) and an example of a feasible configuration (B).

3.1.2 Optimal network design

The goal is to select the best set of 4 sensors, with 27 potential locations, by minimizing the cost function given by equation (8). This function describes the match degree between the concentration given by the model and the observed values measured by the network. The SA algorithm converges to the solutions shown figure 2(a) (blue stars). This result confirms the intuitive one obtained by Rudd *et al*. [14]: best estimated of the source location and strength are obtained with the “line configuration” closest to the source (the relative errors are respectively 3% and 4%). Figure 2(b) shows the evolution of the cost function and the temperature stages. At the first beginning of the process, the cost function oscillates in a fairly large range. After 3000 iterations the oscillations are stabilized and the algorithm reaches the optimal solution.

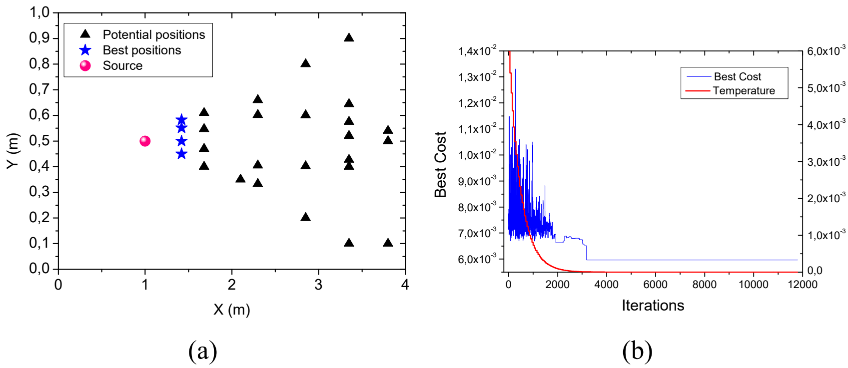

Figure 2: (a) Optimal configuration, (b) Evolution of the cost function (blue line) and of the temperature (red line).

3.1.3 Optimal number of sensors

The optimal number of sensors for this scenario has also been determined (theoretically the minimum number of sensors required to solve this inverse problem is 3). The optimal sets of 3, 4 up to 10 sensors have been first identified by following the previous procedure. Then, for each of these optimal networks, the relative location error (Euclidian distance of the retrieved source from the true source divided by the mean distance between the source and the sensors in the downwind direction) and the relative strength error (difference between the estimate and the true source intensity, divided by the estimate one) have been computed. The results are presented in figure 3. A significant decrease of the relative strength errors is observed when the number of sensors is changed from 3 to 4. This error becomes stable for an optimal network of seven sensors and is observed to be minimal for 6. The relative location error is minimal for 7 sensors.

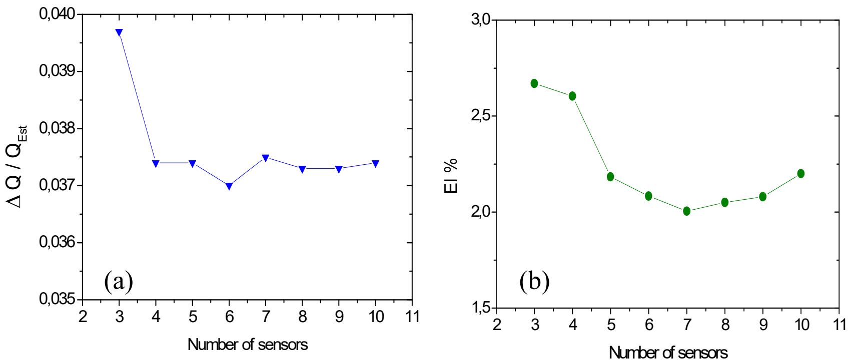

Figure 3: Relative error for (a) strength and (b) location VS number of sensors.

3.2 Evaluation for scenario 2

3.2.1 Optimal network design

The optimal design process for scenario 2 (source anywhere in the domain, network rapidly deployed) is evaluated by using the same framework than for the precious scenario. The goal is to select the best set of 4 sensors, with 27 potential locations. The optimal network must be efficient regardless of the source location. The cost function to be maximized is given by equation (9). It is based on an entropic criterion. The SA algorithm converges to the solutions shown figure 4(a) (blue stars). This result shows that the optimal configuration is far away from the ”domain entrance” with 2 sensors far from the central line of the domain. Geometrically, this configuration allows the monitoring of a large portion of the domain.

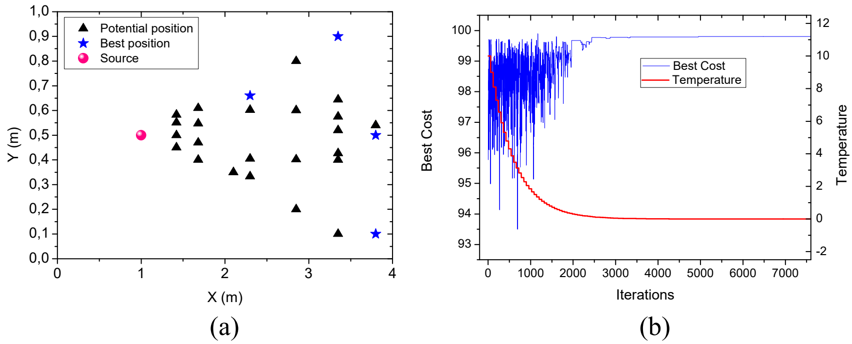

Figure 4: (a) Best four sensors configuration, (b) evolution of cost function.

3.3 Evaluation for scenario 3

3.3.1 Experimental data

The optimal design process for scenario 3 (no a priori knowledge of the source, fixed permanent network) is evaluated with data from the “Pelvoux project” [15]. High frequency wind measurements (figure 5(a)) have been performed, one year

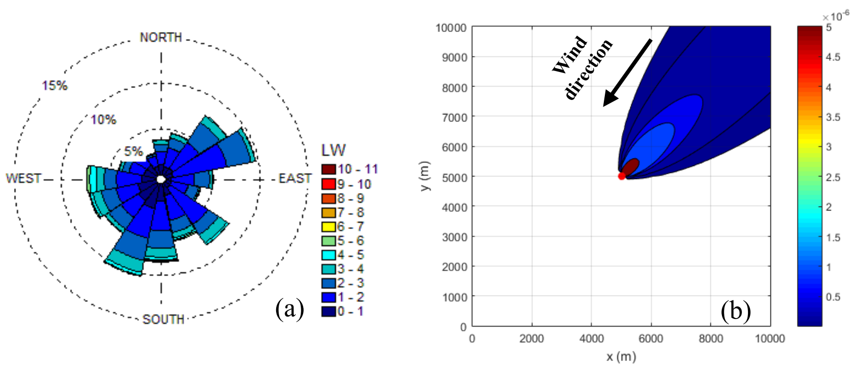

Figure 5: (a) Wind speeds and frequencies for sixteen directions and (b) retroplume for the North–East direction.

long, on the top of a cuboid building located in a typical flat suburban area located in the Paris region (France).

3.3.2 Optimal network design

From the knowledge of the annual meteorological conditions, we seek to obtain the best design of a network of 10 sensors. The optimal network must be efficient regardless of the source location. The potential sensors location are chosen in the “danger zone” surrounding the protected site. This zone is obtained following the procedure described in section 2.3: steady retroplumes are scattered upwind from the site, in the 16 directions (figure 6(a)), over a square domain of dimensions 10×10 km (discretized as a grid of 100×100 cells). To that a Gaussian Plume Model is used with the mean wind speed observed in each direction (figure 5(b)). The lateral and vertical standard deviations are obtained from the Briggs Urban Model. The high ”danger zone” is bounded by taken into account (a) the critical concentration values for the people on the site and (b) the required warning time. By maximizing the cost function given by equation (10), the goal is to select the best set of 10 sensors, within a set of 265 potential locations. The number of 10-combinations of a set of 265 potential locations is around 10^{18}.

3.3.2.1 Determination of potential positions Potential locations for the sensors are all the grid points contained in the danger zones defined with a critical concentration value and a warning time equal to 100 PPM and 10 min respectively (figure 6).

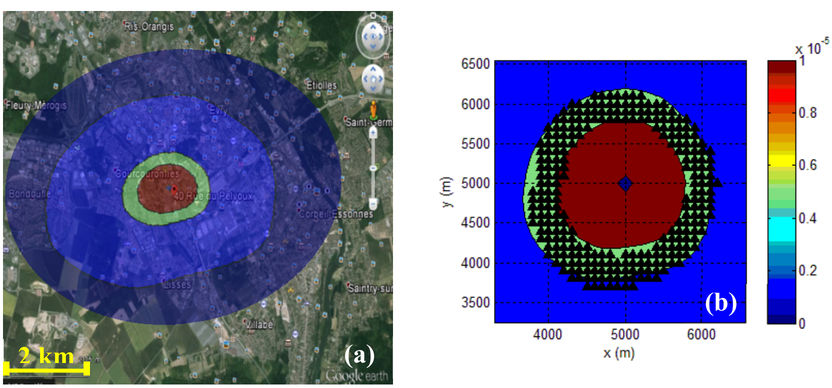

Figure 6: (a) Contours of the danger zone and (b) potential sensors locations (black triangles) surrounding the Pelvoux building.

3.3.2.2 Optimal detectors locations First a parametric study have been performed to set the Simulated Annealing parameters. The most efficient ones are T_0=50, T_s= 10^{-6}, L_M= 40 and θ=0.93. The optimal configuration of 10 sensors selected by SA is shown Figure 7(a). Qualitatively, this design is in coherence with the data provided by the wind distribution: It devotes 3 sensors to monitor the East/North–East direction and 3 sensors to monitor the South/South–West direction. Figure 5(a) shows that these directions are the ones with the highest occurrences (9.6% and 10.3% respectively) and thus are the ones with the highest risk.

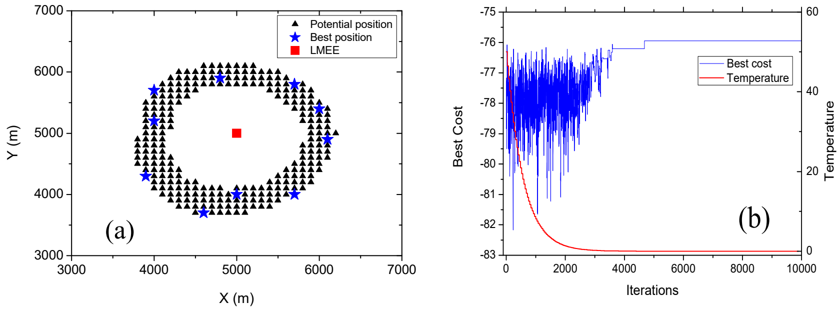

Figure 7: (a) Optimal 10-sensors configuration (blue stars) and (b) evolution of the cost function.

4 Conclusions

This study presents the first application of the renormalized data assimilation method to design optimal sensors networks. This method, associated with an efficient optimization algorithm (SA), has been used to design networks under different scenarios. In each case, the combinatory optimization problem consists of selecting the best set of m locations among a set of n potential locations. The first scenario was to optimize the design a 4-sensors network deployed in emergencies situations, with known meteorological data. The objective was to localize/quantify the source to minimize the error in the measurements forecasts. It has also been shown, that little value is added to the inversion by using more than 7 sensors. The second one was to optimize the design of the same 4-sensors network but in situations where the source has not been yet localized and can be anywhere in the domain. To that, an entropic criterion has been used and the optimal network provides the monitoring of the whole domain. The last one was to optimize the design of a permanent-fixed network of 10 detectors. The objective was to localize/quantify the source with varying meteorological conditions (statistically known). The optimal design, resulting from an entropic criterion, is in coherence with the meteo data. As a perspective of this study, the process should be extend to find the optimal number of sensors required for an effective characterization of the sources. Moreover, in this study, the adjoint source-receptor relationships have been computed by using an analytical Gaussian model. This simple model is not able to capture the effects of complex urban geometries on dispersion process. An interesting extension could be to use CFD models which have potential to provide precise and realistic simulations.

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