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Identification of Multiple Outdoor Contaminant Sources with Monitoring Station Data

Yu Xue[1*], *Zhiqiang (John) Zhai*[2]

[1]*School of Civil Engineering, Dalian University of Technology, Dalian, China*
[2]*Department of Civil, Environmental and Architectural Engineering, University of Colorado Boulder, Boulder, Colorado, USA*

Abstract: Identifying contaminant sources in a precise and rapid manner can facilitate proper and effective air quality controls in outdoor environments with airborne infection, fire smoke and chemical pollutant release etc. Probability based inverse modelling method was shown feasible for locating single source. This paper advances the method to identify continuously releasing multiple contaminant sources. The study formulates an inverse modelling algorithm that can promptly locate dynamic source quickly with contaminant information detected by monitoring stations. An open space experiment is employed to verify the prediction. The developed algorithm promptly and accurately identify the source locations.

Key words: *Outdoor Pollutant, Inverse modelling, Multi-source Identification, Fixed Sensors*

INTRODUCTION

Urban air quality exacerbation demands effective control and improvement. Prompt identification of urban pollutant sources can ensure the pollutant sources can be regulated and controlled as well as helping develop appropriate urban development and management strategies. Air quality monitoring stations are developed in cities that report in real time the air quality indices. The information is helpful in understanding current (and historical) pollution conditions at specific locations, however, it does not provide prediction of potential source locations that cause the pollution. High pollution concentration at one location often does not imply possible sources at the same location. Contaminants will travel with the wind (i.e., airflow) all over the cities.

The existing pollutant source tracking methods can be categorized into two general groups: the forward method and the backward method. The forward method is a "simple" but slow approach to identifying potential sources through the traditional "trial-error" process (Gorelick et al. 1983; Vukovic and Srebric 2007). The backward method is a faster approach that starts from the end status and uses negative time step or velocity in the simulation to obtain pollutant concentration evolution and source flux history. Skaggs and Kabala (1995) developed a quasi-reversible (QR) solution to a convection-dispersion equation (CDE) by solving the QR diffusion operator in a moving coordinate system. Zhang and Chen (2007) used this method to identify the source locations and strengths for two- and three-dimensional aircraft cabins with computational fluid dynamics (CFD) techniques. This method requires special schemes to stabilize the solution process and needs prior source information, such as source location and activation time, which is difficult to obtain in actual situations. Wagner (1992) developed a probability based backward method for simultaneous model parameter estimation and source characterization in groundwater. The inverse model combined the groundwater flow and pollutant transport simulation with non-linear maximum likelihood prediction. Neupauer and Wilson (1999) proposed the adjoint method as a formal framework to predict groundwater pollutant source location and travel time probabilities. The method can identify the historical characteristics of contamination in a multidimensional aquifer with complex domain geometries. Lin (2003) implemented this method and improved the prediction accuracy greatly. The improved method has been used to find the pollution source of the groundwater contamination in Massachusetts Military Reservation (MMR). Liu and Zhai (2007) extended this inverse modeling theory to identify indoor airborne pollutant sources. The method is verified to be able to identify indoor pollutant source locations and strengths based on limited information gained from few pollutant sensors.

Most existing forward and backward studies have shown good capability of their algorithms in identifying single pollutant source. Few studies discussed the situation of multiple pollutant sources that is common in real situations. Cai et al. (2012) used the forward method to identify multiple sources, which required a large amount of computational work and prior knowledge. Cai et al. (2014) suggested a rapid method to track multiple constantly-releasing pollutant sources in indoor environments with unknown release time. The method requires a limited number of potential sources with known locations. This paper explores and develops a new algorithm and procedure, based on the adjoint probability method studied before for indoor applications, to identify source locations of multiple constantly-releasing outdoor pollutants, with limited information collected from several location-fixed sensors.

METHODOLOGIES

The multi-source identification approach is developed upon the previously-developed adjoint probability method for location probability identification (Liu and Zhai 2007). With the sensor readings of contaminant concentrations at different locations, the proposed algorithm first solves the adjoint function of the mass transport Equation to obtain location probability of a potential pollutant source base on every single monitoring data. The algorithm then integrates these probabilities and predicts the contaminant source strength and location. Instead of installing multiple "static" sensors at specified locations in the domain of interest or rely on movable sensors, this study proposes to use existing sensors equipped to Meteorological Monitoring Stations.

The new algorithm follows the procedure below to identify sources using the location-fixed sensors:

(1) The algorithm starts with the presumption that only one source exists in the field. Three sensors are selected to detect the pollutant concentration. The principle to select proper sensors is that the detected pollutant concentration should vary by at least 20% from each other. Then the location of the sensors, pollutant concentration detected by the sensors, and air velocity from the weather bureau will be recorded as L1, L2 and L3. The algorithm does not recommend L1, L2, and L3 locations sit on the same line. Measurement locations on one line may result in multiple possible source locations or no solution for the algorithm.

(2) Solve Equations (2) - (7) with the recorded wind velocity information on the outdoor site. Identify the possible first source location S1(1) and strength C1(1) with the adjoint method based on the recorded information of L1, L2 and L3, mark it on the "map" as S1(1).

(3) Track along the wind direction from the marked S1(1) to find another three nearest sensors, record their locations and contaminant concentration, repeat step (2) to have the second try to identify the possible first source location S1(2) and its strength C1(2).

(4) If the location S1(2) is far away from S1(1), it means that there are more than one contaminant sources. Repeat step (3) until S1(n+1) is very close to S1(n) (n=1, 2, 3,…), which means the first source location is S1(n+1) and its strength is C1(n+1). Researchers can head to the location S1(n+1) to confirm the accurate location and strength, or just use the identified value as the actual value.

(5) When the first source is identified, simulate the corresponding concentration field using Equation (1), including the locations of L1, L2 and L3 et al. Since Equation (1) is a linear equation with the fixed velocity field, this first simulated pollutant concentration field can be subtracted from the former test data. Then repeat Steps (2) – (4) with the new concentration information until all detected concentrations are smaller than the threshold.

(6) To confirm the result, the progress advises researchers repeat the procedure when the velocity magnitude and direction of the field is significantly different.

CASE STUDY

An ideal and simple open space case is used to demonstrate and verify the developed algorithm and program. The 2-D open field has a size of 2 km×2 km with a 2 m/s north wind (shown in Figure 1). The study uses the forward simulation result as the “actual” situation for validation. In the forward simulation, the sources’ strengths are set to 100 unit/(m^3·s). Sensors locate randomly in the field (as shown in Figure 1). To deliberately consider and mimic the disparity between simulation and reality, the backward simulation uses a different and coarse mesh when identifying the pollutant sources. In addition, the potential measurement errors are included in the prediction where the values of C1, C2 and C3 are given the uncertainty of 10%, which implies the sensor has 10% inaccuracy.

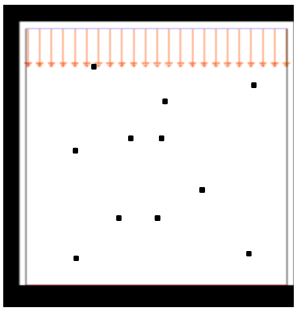
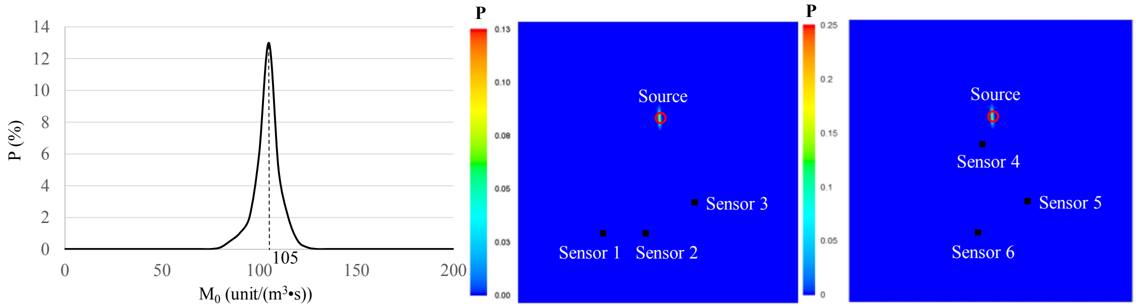


Figure 1. The open space with sensors



(a) (b) (c)

Figure 2. Identification of single pollutant source: (a) Largest probability corresponding different assumed source strength; (b) The first trial to identify the source; (c) The second trial to identify the source

The study first tests the scenario with only one pollutant source. Figure 2 shows the contour of the predicted source location probability (the figure just shows the selected sensors for tracking sources). The real source is located at the red circle. The algorithm tracks the source precisely with two trials. In the first trial, the largest probability in the field corresponding different assumed source strength is shown as in Figure 2(a) (Every trial will obtain a similar curve as shown in Figure 2(a), the only difference between different cases is the biggest probability number and its corresponding strength M_0, so in the following cases the curve will not be shown again). The source strength with biggest probability is 105 unit/(m^3·s) which is adopted as the identified source strength for the first trial. And the corresponding location is shown in Figure 2(b). Then with the guidance of step 3, the algorithm selected another three sensors and located the source with the second trial (as shown in Figure 2(b)). Both two trials identifies the same location. It means there is only one source in the field. The identified source strength is 105 unit/(m^3·s), which is very close to the prescribed source strength in the forward simulation.

The study then models the scenario with two pollutant sources. Figure 3(a) shows the “actual” condition of the pollution field. According to Step (1) and (2), the first trial identifies a location S1(1) as seen in Figure 3(b). Then the algorithm selects another three sensors (sensor 4 to 6) at the downwind location of S1(1). With data of sensor 4 to 6, the algorithm identifies another location S1(2) (as shown in Figure 3(c)). S1(2) is far away from S1(1), so there are more than one pollutant sources. Repeat step 3 and the algorithm gets the third result S1(3). S1(3) is almost coincide with S1(2) (as shown in Figure 3(d)). So the algorithm regard S1(3) as the location of Source 1. Researchers can search around S1(3) to confirm the accurate location and strength of Source 1. The paper here just adopts the identified value S1(3) and

C1(3) (105 unit/(m^3·s), which is very close to the actual value). With the identified location and strength of Source 1, Step (5) is performed to simulate the pollution field caused by Source 1 as shown in Figure 3(e). The pollution concentrations at all sensors by Source 1 can be obtained from the simulated result: C1 (Source 1), C2 (Source 1) and C3 (Source 1) et al. as shown in Figure 3(d). The study can then produce the new $C1(\text{new}) = C1 - C1(\text{Source1})$, and C2 (new) and C3 (new) et al., respectively. Source 2 is identified using the updated pollutant concentrations as shown in Figure 3(f) and Figure 3(g). The identified location of Sensor 2 is S2(2) and the strength is C2(2) 100 unit/(m^3•s). After simulating and subtracting the pollution caused by Source 1 and Source 2 from data of sensors, sensors' data of contaminant concentration are quite small which can be ignored. So, the study assures that all sources has been identified. The study succeeds in identifying pollutant sources in more complicated cases, such as the case with six sources as shown in Figure 3(h).

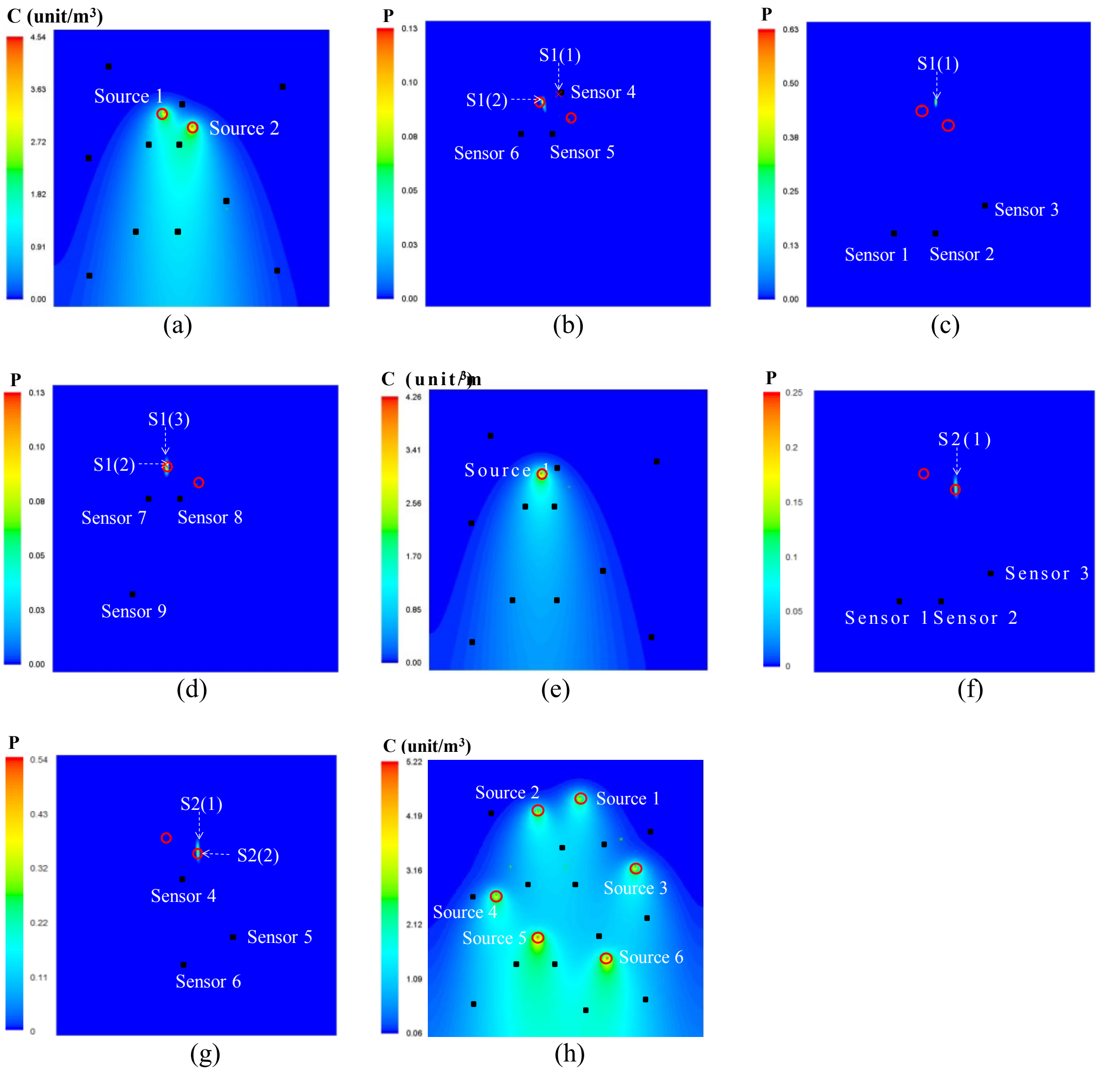


Figure 3. Identification of multiple pollutant sources in an open space: (a) "Actual" condition with two sources; (b) The first trial for S1 get S1(1); (c) The second trial for S1 gets S1(2); (d) The third trial for S1 gets S1(3); (e) Simulated pollution field by Source 1 (f) The first trial for S2 gets S2(1); (g) The second trial for S2 gets S2(2); (h) Case with six pollutant sources.

DISCUSSION AND CONCLUSION

This method is incapacity for linear and facial sources, so for the case, the study chose separated pollutant sources. If researchers can estimate the average strength of it, the algorithm can treat them as background contaminant concentration and decrease the influence of it for source tracking. Because of the limited number of sensors, the algorithm can only obtain approximate location of sources. If researchers need to get the accurate location and strength of sources, there should be much more sensors, or they can integrate this method with movable sensors. The more accurate results researchers want to get, the more accurate building model and contaminant information should be obtained.

The developed method can be used to locate various complicated pollution scenarios, such as to identify transient urban pollutant sources, as well as combined with movable sensors for more agile and high accuracy tracking procedure.

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