A Study on the Estimation of Leakage Source Term by Outdoor Radiation Fixed Monitor

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1. Introduction

Rapid emergency response is critical to protect the lives and property of residents if toxic substances are released into the atmosphere and spread widely under intentional or accidental circumstances. It is important to model atmospheric diffusion of scattered materials in various scenarios and the phenomenon of diffusion [1] . It is important to know the extent of diffusion and initial location of leakage of contaminants over time for rapid emergency response to radioactive material release. Most of the spread may not be clear if it is invisible, making it difficult or impossible to observe in a visual way. In such cases, ground detectors installed to monitor the relevant substances form a network of interconnected objects in a fixed state and can sometimes be installed in mobile devices to detect emissions. [2] In such cases, ground detectors installed to monitor the relevant substances form a network of interconnected objects in a fixed state and can sometimes be installed in mobile devices to detect emissions.[3] Overseas paper data on various methods to optimize the estimation of the initial radioactive material source term in the event of an accident due to leakage of radioactive materials were reviewed. Based on the atmospheric diffusion model of radioactive materials, a novel attempt on the backtracking method was verified through the Copenhagen experiment.

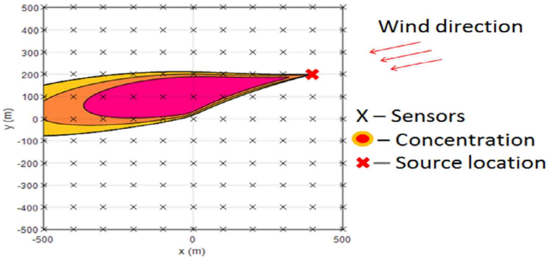

Fig 1 Example of a static sensor network

2. Methods and Results

In this section some of the techniques used to model the detector channel are described. The channel model includes a SiC detector, cable, preamplifier, amplifier, and discriminator models.

2.1 *Diffusion model*

The transport and diffusion models of airborne substances are used to estimate the diffusion of pollutants into the atmosphere. The models currently used are diverse in terms of applicable scenarios, contextual assumptions, and complexity. It is applied to the Gaussian plume model, which is widely used throughout the literature of source term estimation due to its simplicity and fast calculation [4]. The main parameters represent atmospheric turbulence coefficients and standard deviations that account for crosswinds and vertical mixing of pollutants. In a popular approach based on Pasquill's atmospheric stability rating, there are several derived outcomes of these values [5]. Gaussian plume's equation is derived from the turbulent diffusion equation assuming a uniform steady-state flow and a steady-state point source and uses the following equation.

$$C(x,y,z,Q)=\frac{Q}{\bar{u}\,\sigma_y\sigma_z 2\pi}\left(\frac{-y^2}{2\sigma_y^2}\right)\left[\exp\left(\frac{-(z-h)^2}{2\sigma_z^2}\right)+\exp\left(\frac{-(z+h)^2}{2\sigma_z^2}\right)\right]$$

where C is the concentration of radioactive materials at the detector or measured location, Q is the emission rate, and x, y, z are the downwind, crosswind, and vertical distance are the average wind velocity at height h emitted [6] Extended models in the Gaussian plume model are being used to overcome restrictive assumptions such as the Gaussian puff-model.

The forward diffusion problem can be defined as predicting the response of a system using physical theory and system parameters. In the inverse modeling problem, inference is made on the value of the system parameters based on the observation of the system response. In short, the problem of backtracking can be formulated as follows [7].

$$m \approx F^{-1}(d)$$

2.2 *Bayesian inference*

where d is the observed value, m is the forward diffusion model parameter, and function F is the forward model that controls the system response. Because small changes in d can lead to large changes in m, the backtracking problem may have poor conditions. The current event reconstruction problem requires estimating the model parameter m given the observed concentration in the detector network. Both deterministic and stochastic approaches have been developed following the application of the backtracking problem to solve the problem[8].

$$Posterior \propto \frac{Prior \times Likelihood}{Evidence}$$

It is important because it tracks how to obtain concentration observations through likelihood functions in leak event reconstruction problems. The detector cannot reliably quantify the concentration of trace pollutants that may be below the specified detection limit. Therefore, the detector can read the zero concentration value while ignoring the presence of trace pollutants. Therefore, it is important to process the detection value detected as zero. It is possible to assume a probability model in which a trace amount of contaminants are present that may not be detected due to the minimum detection concentration value of the detector. That is, the likelihood function can write an expression as follows when the actual concentration may not be zero.

$$L(d_i|\mathrm{m}) = \int_0^\infty \mathrm{p}(\mathrm{d_i}, \xi_\mathrm{i} \mid \mathrm{m})\, \mathrm{d}\xi_\mathrm{i} = \mathrm{II}[d_i = 0] \int_0^\infty \exp(-\alpha \cdot \mathrm{C_m} \mathrm{p}(\mathrm{d_i}, \xi_\mathrm{i} \mid \mathrm{m})\, \mathrm{d}\xi_\mathrm{i}$$

$$+ \mathrm{II}[d_i > 0] \int_0^\infty [1 - \exp(-\alpha \cdot \mathrm{C_m})] \times p(\xi_i \mid \mathrm{m})\, \delta_{\mathrm{d_i}}(\xi_\mathrm{i}) \mathrm{d}\xi_\mathrm{i},$$

The diffusion coefficients of the y-axis and z-axis of the Gaussian diffusion equation can be determined as follows.

$$\sigma_y = 0.22x(1 + 0.0004x)^{-0.5}, \quad \sigma_z = 0.20x$$

$$\sigma_y = \xi_1 x(1 + 0.0004x)^{-0.5}, \quad \sigma_z = \xi_2 x$$

$$\mathrm{p}(\mathrm{m}|\mathrm{d}) \propto \left\{ \prod_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{L}(\mathrm{d_i} \mid \mathrm{m}) \right\} \times \mathrm{p}(\mathrm{m})$$

$$\mathrm{p}(\mathrm{m}) = \mathrm{p}(\mathrm{x}), \mathrm{p}(\mathrm{y}), \mathrm{p}(\mathrm{Q}), \mathrm{p}(\mathrm{H}), \mathrm{p}(\mathrm{U}), \mathrm{p}(\theta), \mathrm{p}($$

As shown in Figure 2, a forward-diffused Gaussian plume model was used using Markov chain Monte Carlo simulations based on the Metropolis-Hastings sampling algorithm.

$$p(d_i, \xi_i \mid \mathrm{m}) = \frac{1}{\sqrt{2\pi}\sigma\xi_\mathrm{i}} \exp\left(-\frac{1}{2\sigma^2} (\log \xi_i - \log C_m)^2 \right)$$

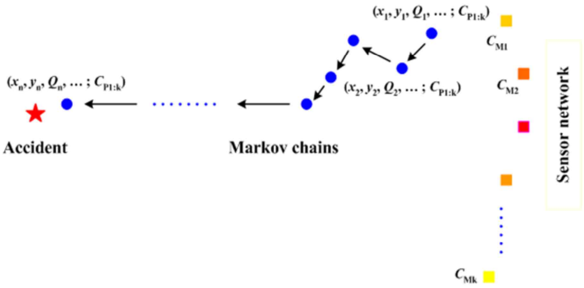

Fig. 2 Schematic diagram of Markov chain Monte Carlo simulation backtracking method based on Metropolis-Hastings sampling algorithm

2.3 Reproduction of an event in a Copenhagen tracker experiment

A series of tracker experiments were conducted in the Copenhagen area in 1978 and 1979. The concentration and weather conditions of tracer hexafluoride (SF6) were measured and reported in Erik and Lyck (2002). [9]. In all experiments, the SF6 tracer was released from a tower 115 m high. The sampler/detector was placed 2–3 m above the ground along three side wind arcs located 2–6 km from the tracer release point. The total sampling time for concentration measurement was 1 hour. In the tracer data corresponding to the experiment conducted on October 19, the detection limit was given as 9 ng m-3, and the values below this limit were marked as 0. This value is used to set the detector threshold Cth in the expression. Stochastic event reconstruction methods. Eight of the 40 samples register zero concentration values marked with clear markers. In the current study, the tracer diffusion experiment has been reconstructed for nine model parameters ($x, y, Q, H, \theta, U, \xi_1, \xi_2, \sigma^2$).

Table 1. Key topics for Copenhagen atmospheric tracking

Input parameter	**Representative**
Release gas	**SF_6**
Release point (km)	**(0, 0)**
Wind speed (m/s)	**8.42**
Source rate (g/s)	**3.2**
Wind direction (deg)	**293***
Stability class	**C**
Detection limit (ng/m^3)	**9**

3. Conclusions

The reconstruction problem of atmospheric diffusion events was identified by mathematical modeling through a source term reconstruction procedure using a fixed monitor. Fixed radiation monitoring devices are widely used in emergency response applications due to the advantages of early detection. It was useful to use a fixed detector for the radiation source accident inverse estimation algorithm.

Repeated calculations require a lot of computational time, and for this reason, many studies have used simple Gaussian Plume equations as the underlying diffusion model.

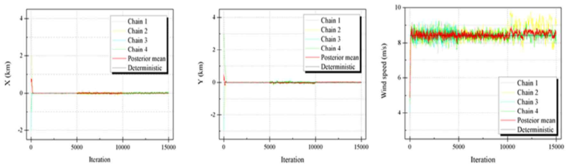

Fig. 3 Results of tracking the release position of the source

In fact, even complex diffusion models have significantly lost accuracy on real-world data and have had distinct problems in estimating emission rates. It can be seen that the use of mobile monitors that can provide radiological source leakage location estimation without error in back-tracking modeling is effective. Much more data is needed than can be provided by fixed networks, and mobile monitors can collect data from more suitable locations. Research on source leakage estimation has focused on improving existing methods to reduce computational time, which is an important factor in emergency response.

Reducing search space and good initial estimation are most effective in reducing computation by reducing the required number of iterations and the number of diffusion model runs.

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