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Author
Sohn, Michael D.

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Michael D. Sohn and David M. Lorenzetti

Indoor Environment Department
Lawrence Berkeley National Laboratory
One Cyclotron Road, Mail Stop: 90R3058
Berkeley, California, 94720, USA

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Michael D. Sohn* and David M. Lorenzetti

Indoor Environment Department
Lawrence Berkeley National Laboratory
One Cyclotron Road, Mail Stop: 90R3058
Berkeley, California, 94720, USA

**Corresponding author email: mdsohn@lbl.gov*

ABSTRACT

Contaminant releases in or near a building can lead to significant human exposures unless prompt response is taken. U.S. Federal and local agencies are implementing programs to place air-monitoring samplers in buildings to quickly detect biological agents. We describe a probabilistic algorithm for siting samplers in order to detect accidental or intentional releases of biological material. The algorithm maximizes the probability of detecting a release from among a suite of realistic scenarios. The scenarios may differ in any unknown, for example the release size or location, weather, mode of building operation, etc. The algorithm also can optimize sampler placement in the face of modeling uncertainties, for example the airflow leakage characteristics of the building, and the detection capabilities of the samplers. In an illustrative example, we apply the algorithm to a hypothetical 24-room commercial building, finding optimal networks for a variety of assumed sampler types and performance characteristics. We also discuss extensions of this work for detecting ambient pollutants in buildings, and for understanding building-wide airflow, pollutant dispersion, and exposures.

INTRODUCTION

Private and public agencies are rapidly implementing programs to detect accidental or intentional releases of hazardous agents in buildings and outdoors. For biological agents, such as viruses, spores, and bacteria, these programs use samplers that draw ambient air through a filter for later analysis.

The greatest impediment to designing such a detection system is the uncertainty surrounding a potential event. In buildings, for example, the weather, release particulars (location, amount, timing, etc.), and mode of building operation all affect the transport and fate of the agent. Furthermore, the variables of interest can interact, for instance when outside ventilation rates change based on the outside air temperature and humidity. Finally, even if all such conditions are known, uncertainty in the transport and fate model may reduce confidence in the predicted performance of the sampler network.

This paper explores the design goal of maximizing the probability of detecting a release. Specifically, the system should place and operate the sampling equipment in order to maximize the chance of detecting a release from a suite of relevant scenarios, subject to constraints such as the number and type of samplers, maintenance costs, and so on. Moreover, the system should avoid excessive sensitivity to highly unlikely scenarios (for instance, a release in a secure area of the building), if that leads to worse performance under more likely conditions (for instance, a release at a ground-level air intake).

The probabilistic approach presented here differs from traditional optimization techniques by explicitly accounting for the relative likelihoods associated with uncertain, variable, and interdependent conditions such as those described above.

We exercise the algorithm on a hypothetical application, and answer the following questions: What sampler placements maximize the probability of detecting a biological release, given the uncertainties and variability in the building and release conditions? How does that probability improve with additional samplers? And what sampler characteristics maximize the detection probability?

METHODS

We seek to identify the sampler network with the greatest probability of detecting a release in a building. Samplers are integrating detectors, for example continuously drawing air through a filter which is replaced and analyzed daily. Our approach is based on identifying all plausible releases (location, amount, and time of day), modes of building operation, meteorological conditions, and any other uncertainty that may affect the sampler system. These possible events combine to form a large number of design scenarios, each with an identified probability of occurrence.

The algorithm combines event-tree analysis, transport and fate modeling, and numerical optimization. The event tree identifies the design scenarios and their probabilities of occurrence. The transport model predicts, for each scenario, the agent mass collected by hypothetical samplers throughout the building. These agent mass predictions give the probability that a single sampler would detect each scenario. Finally, the optimization step finds the sampler networks that maximize the expected probability of detecting a release from among all the design scenarios.

The following subsections describe these components of the algorithm. For additional details, see [1].

Event tree

The event tree enumerates all plausible design scenarios, and determines the relative likelihood that each will occur. Each scenario represents a particular set of choices for the uncertain parameters and variable conditions. The sampler placements will be optimized over all the scenarios, so realistic scenario probabilities ensure that unlikely events do not dominate the network design. Similarly, under- or over-representing the variability of a model input may improperly skew the sampler placements, so it is important to consider the full range of scenarios as well as their occurrence probabilities.

Each branch of the event tree is assigned a probability of occurrence. Let $\alpha_i^{\,j}$ represent the j^{th} possible value that event α_i can take. Then $P(\alpha_i^{\,j})$ is the probability of $\alpha_i^{\,j}$ occurring on the particular subtree of interest. For independent events, the $P(\alpha_i^{\,j})$ do not vary from subtree to subtree.

The probabilities on each subtree are normalized so that

$$\sum_j P(\alpha_i{}^j) = 1 \qquad (1)$$

In other words, every subtree has a branch for every condition against which the sampler network should be optimized.

Each final outcome (leaf) of the event tree represents a scenario that will be presented to the optimization algorithm. For an event tree with N stages, the likelihood of scenario k is the product of the N branch probabilities:

$$L_k = \prod_{i=1}^{N} P(\alpha_i{}^{A_i}) \qquad (2)$$

where A_i denotes the actual choice that scenario k makes for event α_i. Normalizing the event probabilities as in Equation 1 guarantees

$$\sum_{k=1}^{K} L_k = 1 \qquad (3)$$

where K gives the number of scenarios. In other words, the input to the optimization step covers every event of interest.

Transport and fate

To evaluate how a sampler would perform under each scenario, we predict the mass that it would collect, based on its location and filter replacement schedule. Then we convert that mass to a probability of detecting the release. In the illustrative application that follows, we used the COMIS multizone airflow and pollutant dispersion model [2]. COMIS represents a building as a collection of well-mixed zones, connected by flow paths such as cracks, doors, windows, and ductwork. The program computes airflow through the paths by balancing pressures between the zones, and finds the time-dependent pollutant transport that results from the steady-state airflows.

Because the network optimization depends on the model predictions, it is important to acknowledge that building transport and fate models carry a great deal of uncertainty due to parameter uncertainty, variability, and inherent model misspecification errors. Care must be taken to perform sensitivity analyses, to validate the important model processes, and to inspect the network results for clues to how they depend on model assumptions.

Sampler performance

The mass captured by a sampler depends on the time history of the airborne concentration, the filter efficiency, and the rate of airflow through the filter. The probability of detecting a release is driven largely by: (1) the mass on the filter; (2) the capability of the analytical procedure; (3) fouling, for instance with other types of particles; and (4) the acceptability of false positives and false negatives. To a certain extent, these factors interact. For example, with very little agent mass on the filter, there is a greater chance that fouling will interfere with the analysis. Similarly, a low tolerance for false positives may place greater demands on the analysis to confirm suspected sampler hits. In the example that follows, we optimize networks against several hypothetical samplers.

Network optimization

We find the optimal network of samplers by brute force: for a given number of samplers, we examine every possible deployment of those samplers among all the rooms in the building. While other optimization strategies are possible, this approach ensures we find the best network, and allows us to list alternate networks with near-optimal detection. Note that we allow the co-location of multiple samplers in one room (mathematically, we generate the sampler combinations with replacement).

For each scenario, the probability that a candidate sampler network y will detect a release is the probability of one or more samplers in the network detecting it. Thus

$$P(\text{network } y \text{ alarms}) = 1 - P(\text{no samplers in } y \text{ alarm}) \qquad (4)$$

The probability that network y will detect any of the K scenarios is

$$\sum_{k=1}^{K} L_k \times P(\text{network } y \text{ alarms}) \qquad (5)$$

This calculation is repeated for all candidate networks. We then interrogate the results to determine which networks have the highest probability of detecting a release, which scenarios are particularly difficult to detect, which locations in the building are difficult to monitor, and so forth.

ILLUSTRATIVE EXAMPLE

We demonstrate the algorithm by placing 24-hour samplers in a hypothetical single-floor building consisting of a conference room, 20 smaller rooms, and three hallways (Figure 1).

Three mechanical heating, ventilation, and air-conditioning (HVAC) systems serve the building. HVAC1 ventilates the conference room (Room 21) and Hall 1; HVAC2 ventilates Rooms 1-10 and Hall 2; and HVAC3 ventilates Rooms 11-20 and Hall 3. The bathrooms (Rooms 1 and 11) both have exhaust fans to the outside. While the three ventilation systems are not connected, cross-contamination does occur due to airflows between rooms and hallways.

Several of the modeling choices were made to simplify the analysis for demonstration purposes. In a real building, ventilation flow rates change throughout the day, wind blows from different directions, temperatures differ by location and time of day, leakages vary by location, and so forth. These effects can be included in real studies by modeling building-specific details, and by sampling from appropriate statistical distributions.

Event probabilities

We considered each room and hallway as a possible release location, with release amounts ranging from 1 mg to 50 g, and release times distributed throughout the day.

We assumed that event probabilities are independent, and hence identical from subtree to subtree within the event tree. The resulting tree yields 7920 scenarios, i.e., 7920 combinations of source location, release mass, and release time over which the network optimization was performed.

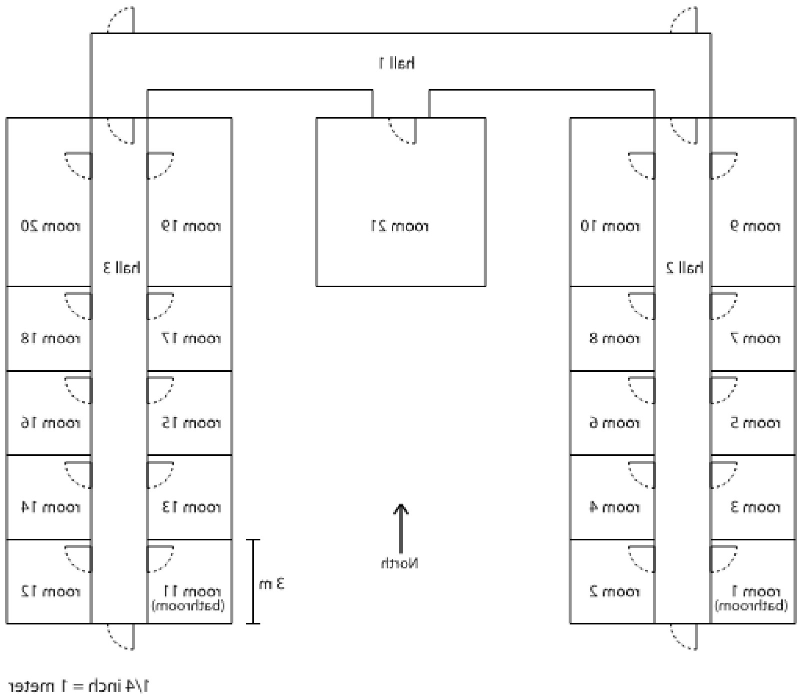

Figure 1. Floor plan (excluding the ventilation supply and return spaces).

Numerical implementation

Using COMIS, we simulated the pollutant dispersion for all 7920 scenarios. Next we converted the filtered mass into detection probabilities, using the hypothetical sampler performance curves of Figure 2. The curves show, for a given agent mass on the filter, the probability that the agent will be detected. Curve 1, with its sharp transition from non-detection to detection, produces mostly clear misses or hits (i.e., probability ~0 or ~1). Curve 8, on the other hand, makes a broader transition. Therefore it results in many cases with an intermediate probability of detection.

Results

For each sampler performance curve, we optimized networks of one to seven samplers. Figure 3 shows the results. For instance, using a single sampler from curve 1, the best network detects 63% of the scenarios. Using two samplers from curve 1 raises the detection probability to 99%. On the other hand, with two samplers from curve 8, the best network has only a 26 % chance of detecting a scenario.

Table 1 lists the optimal sampler locations for the smallest network able to detect a scenario at least 75 % of the time (not all sampler types achieve this cutoff). For curve 1, the smallest acceptable network has samplers in rooms 1 and 11 - the bathrooms in the west and east wings. The algorithm selects these locations because of their unique ventilation setup. The bathroom fans exhaust 10% more air to the outdoors than is supplied by the ventilation system. Therefore detecting an agent release in a bathroom requires sampling air from the bathroom. At the same time, the bathrooms pull in air from all the other spaces, via the ventilation system and the hallways. Thus, a relatively sensitive sampler, such as defined by curve 1, can detect many releases based on the small amount of contaminant mass that exits the building through the bathrooms.

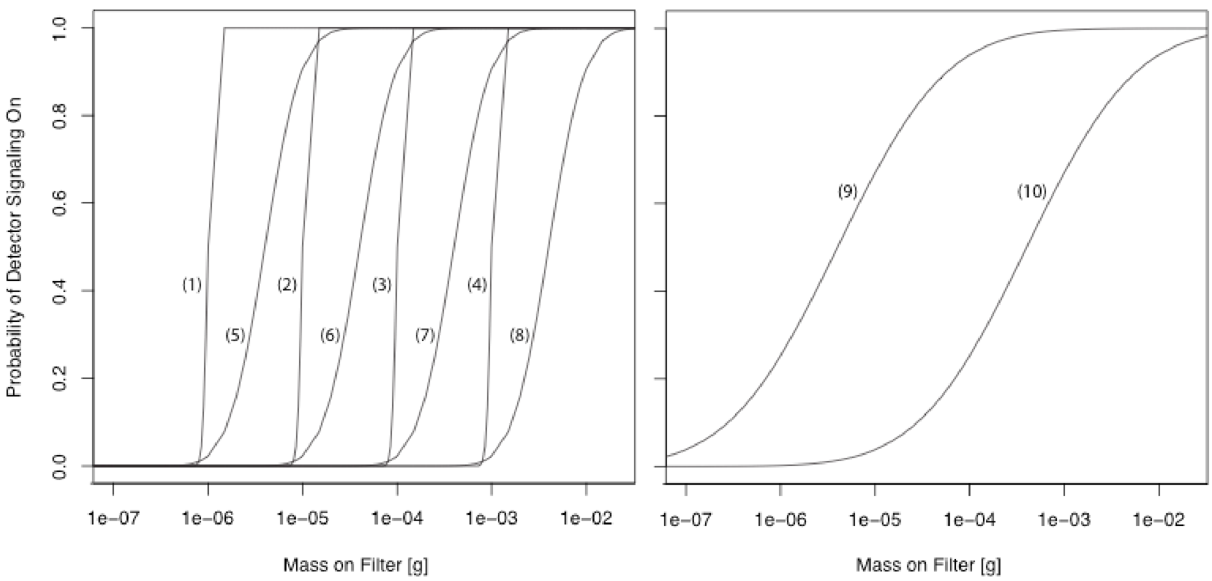

Figure 2: Sampler performance curves for 10 candidate analysis methods (hypothetical).

In fact, the top four networks in Table 1 all use this same configuration. The first network to break the pattern is for curve 6. It also uses two samplers, but places them in the ventilation return systems for the west and east wings. Curve 6 is not sensitive enough to detect releases from around the building, simply by sampling air from the bathrooms. Like the bathroom exhausts, the ventilation return systems collect air from all around the building, but in much greater quantities. Therefore the return systems are favored by networks with less-sensitive samplers.

Table 1. Minimum number of samplers needed to achieve at least 75% detection probability.

Curve	Probability	Optimal Sampler Locations					
1	99%	Room 1	Room 11				
5	96%	Room 1	Room 11				
9	94%	Room 1	Room 11				
2	92%	Room 1	Room 11				
6	82%	Return-E	Return-W				
3	80%	Return-E	Return-W	Return-N			
10	76%	Return-E	Return-E	Return-W	Return-W	Room 1	Room 11

The last row in Table 1 shows that the algorithm may place multiple samplers in a single location. Using six samplers from curve 10, the best network has two samplers each in the east and west ventilation return systems. For samplers with a soft transition from probability zero to one, adding a second sampler in a critical location may increase the network detection probability more than placing the same sampler in a completely different location.

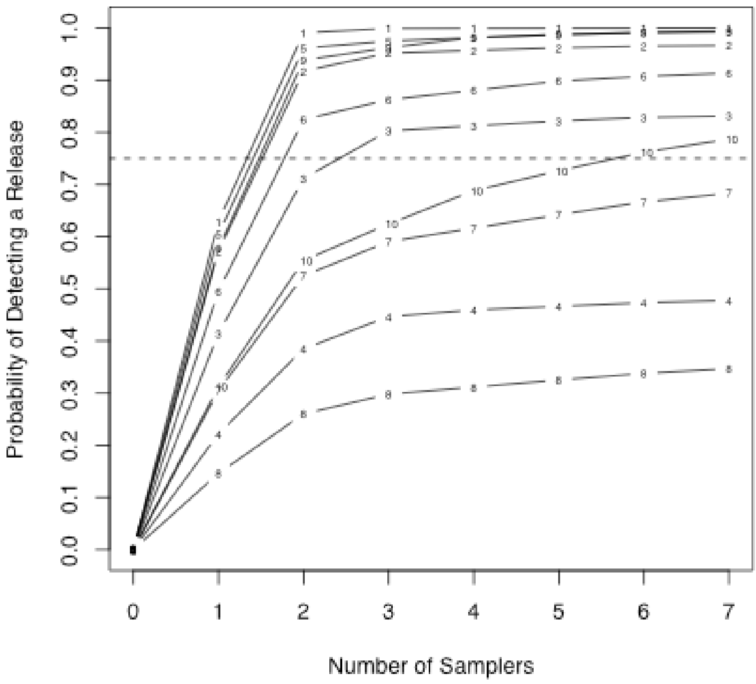

Figure 3: Expected time to detect an attack with a sampler placed in return 1 and return 2.

CONCLUSIONS AND DISCUSSION

This paper outlines a probabilistic approach to siting samplers for detecting accidental or intentional biological releases. The user defines a number of scenarios, which may differ in any uncertain variable—the release size and location, type of agent, weather, building operation, leakage parameters, and so on. In addition, the user quantifies the relative probability of each scenario. The algorithm then identifies those sampler networks with the highest probability of detecting a release from the suite.

The algorithm provides a rigorous approach to handling uncertainty in the transport and fate of the biological material. It avoids placing undue emphasis on highly unlikely scenarios (with the associated risk of failing to detect more likely releases). Finally, it makes explicit all assumptions about the nature and relative importance of the threat scenarios. Thus it encourages thorough exploration of the design space, from comparing sampler characteristics (cost, detection threshold, rates of false positive and false negatives, etc.), to “hardening” a building by changing its setup and operation, to assessing the relative benefits of adding a sampler to different facilities.

The probabilistic approach does require careful attention to the transport and fate calculations. Clearly the airflow and pollutant dispersion model should be validated against the building of interest (although time-integrated mass predictions require less temporal fidelity than required, say, to interpret real-time chemical sensors [3]).

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