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Systems approach to evaluating sensor characteristics for real-time monitoring of high-risk indoor contaminant releases

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Abstract

Rapid detection of toxic agents in the indoor environment is essential for protecting building occupants from accidental or intentional releases. While there is much research dedicated to designing sensors to detect airborne toxic contaminants, little research has addressed how to incorporate such sensors into a monitoring system designed to protect building occupants. To design sensor systems, one must quantify design tradeoffs, such as response time and accuracy, and select values to optimize the performance of an overall system. We illustrate the importance of a systems approach for properly evaluating such tradeoffs, using data from tracer gas experiments conducted in a three-floor building at the Dugway Proving Grounds, Utah. We explore how well a Bayesian interpretation approach can characterize an indoor release using threshold sensor data. We use this approach to assess the effects of various sensor characteristics, such as response time, threshold level, and accuracy, on overall system performance. The system performance is evaluated in terms of the time needed to characterize the release (location, amount released, and duration). We demonstrate that a systems perspective enables selecting sensor characteristics that optimize the system as a whole.

Keywords: Sensor system; Chemical sensor; Inverse modeling; Bayes Monte Carlo; Buildings

1. Introduction

The sudden release of a toxic agent indoors can pose an acute health threat to building occupants. Consequently, it is of interest to devise indoor air monitoring systems that can detect, locate, and characterize accidental or deliberate toxic gas releases. However, developing such a system is complicated by several requirements. To limit the adverse impacts of the release, the monitoring system must detect and characterize releases in real time. Furthermore, the system must be robust against sensor error, such as false positive or negative measurements.

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Much effort is being directed to the development of toxic chemical sensors. However, relatively little attention has been devoted to identifying and selecting sensors characteristics that will optimize

the performance of sensor systems designed to protect occupants in indoor environments. More over, journal publications on improving chemical protection within indoor environments almost ex clusively focus on optimizing the performance of sensors individually (e.g., electronic noses and robotic systems for plume tracking). The proceed ings of a recent Indoor Air conference (2002) contained only two papers out of 726 that discussed how to design monitoring systems that protect building occupants from toxic releases. The pro ceedings of the 2004 IEEE Sensors conference contained no papers on this topic.

Commercial buildings commonly have monitor ing systems for fire protection, security, and control of heating, ventilating and air conditioning (HVAC) equipment. Advances in microprocessor computing, networking, sensor technology, and artificial intelli gence have helped foster a movement toward automated control of building systems and intelli gent building systems (Piette et al., 2001; Kintner Meyer et al., 2002; Liu and Kim, 2003; Jablonski et al., 2004). Despite rapid advances in these areas, systems that incorporate real-time information about indoor air pollutants have thus far been restricted mainly to ventilation control and energy management utilizing carbon dioxide sensors (Fisk and De Almeida, 1998).

Sohn et al. (2002a) demonstrated a Bayesian interpretation scheme for real-time reconstruction of an indoor contaminant release. That study used synthetic data from a single, small building. A follow-up study used real tracer-gas data in a three story building (Sohn et al., 2002b). In both of these investigations, the sensors were assumed to be capable of reporting continuous concentration measurements.

This paper advances the earlier work by focusing on trigger- or alarm-type sensors, rather than continuous-output devices. A case-study approach is employed, using data from one of 12 tracer-gas experiments conducted at a three-story, 660 m^3 building at the Dugway Proving Ground, Utah (Sextro et al., 1999). Through a series of examples, we examine how well various sensor systems, each system consisting of sensors with different sensor characteristics (threshold level, response time, and accuracy), reconstruct the release event. These examples demonstrate the importance of a systems perspective in selecting sensors with desirable sensor characteristics.

In addition to those already cited, only a few other published studies are closely related to the subject of this paper. Bayesian methods have been proposed for interpreting data from accidental radioactivity releases into outdoor air (Smith and French, 1993; Politis and Robertson, 2004); and for improving uncertainty estimates in Lagrangian photochemical air quality models (Bergin and Milford, 2000). Federspiel (1997) proposed a Kalman filter method to infer emission source strengths based on measured concentrations in a multizone building. A few studies have explored optimal sensor placement within a building for monitoring high-risk release events (Arvelo et al., 2002; Whicker et al., 2003).

2. Approach

We consider the following problem. A finite quantity of a contaminant is released, over a short duration, somewhere in a building (this may include its indoor air intake vents). A network of threshold or alarm-type sensors operates to detect the contaminant. We seek to understand how sensor characteristics such as threshold level and response time affect the ability of a sensor interpretation algorithm to quickly detect and characterize the contaminant release.

The indoor environment of the building is modeled as a system of independent, well-mixed zones interconnected by flow paths. The outdoor environment is represented as an additional zone of infinite size. A mechanical air-handling unit (AHU) operates to extract air from return-air zones, possibly incorporates outdoor air, and discharges the mixture to supply zones. The contaminant is assumed to behave as an ideal tracer.

For the purposes of this paper, we assumed that each zone is equipped with one sensor, and each sensor has a single threshold, meaning the output is either "below threshold" or "above threshold." We define several possible threshold levels that are at or above the minimum detection limit of the sensor. Three important parameters characterize sensor performance in this study: threshold level; response time (also sometimes called integration time); and accuracy.

A sufficiently large release will trigger one or more sensors. A Bayes Monte Carlo algorithm is then initiated to determine key information about the release event, including the location of the release and the contaminant mass discharged. This information can help guide emergency response and post-event remediation.

A two-stage Bayes Monte Carlo algorithm for signal interpretation was presented in Sohn et al. (2002a,b) and is summarized here. The first stage consists of developing a library of hypothetical contaminant transport simulations spanning the set of all plausible pollutant release and internal airflow conditions. In the second stage, the sensor data are interpreted by estimating their degree of statistical agreement with predictions in the simulation library. In an operational system, the interpretation would occur in real time, as the data stream in from sensors. A key virtue of this two-stage algorithm is that the computationally intensive effort to solve the contaminant transport equations for a large number of simulations takes place once, before an event. Because the second stage has modest computational requirements, the monitoring system is capable of real-time data interpretation.

Bayes' rule provides a statistical method for estimating the level of agreement between the observed data and predictions from each of the simulations in the library. A posterior probability states the relative agreement of a given simulation with the observed data. This in turn allows us to estimate uncertain input parameters such as the release location and release conditions or character istics.

The posterior probability of the kth simulation making prediction Y_k, given sensor measurements O, is denoted as $p(Y_k|O)$. Bayes' rule gives $p(Y_k|O)$ as

$$p(Y_k|O) = \frac{p(O|Y_k)p(Y_k)}{\sum_{i=1}^{N} p(O|Y_i)p(Y_i)}, \quad (1)$$

where $p(O|Y_k)$ is the likelihood of observing measurements O given simulation prediction Y_k, $p(Y_k)$ is the prior probability of the kth simulation (that is, an a priori estimate of the probability of the kth simulation), and N is the total number of simulations in the library. Note that O and Y_k are vectors.

The likelihood function, $p(O|Y_k)$, reflects the error structure of the data. In general, errors can result from measurement inaccuracy or imprecision, correlation errors and imperfect model representa tion. In practice, deriving a likelihood function will require careful work. For example, if sensors contain calibration drift, or if errors are correlated with time owing to the presence of an interfering chemical, then the likelihood function must account for the diminished quality of the data as a function of time. Sohn et al. (2000, 2002a) and Brand and Small (1995) describe the implementation of Bayes Monte Carlo updating in more detail, and discuss alternatives for evaluating the likelihood function. Qian et al. (2003) also discuss the likelihood function and compare the Bayes Monte Carlo approach to Bayesian updating with Markov-chain Monte Carlo integration.

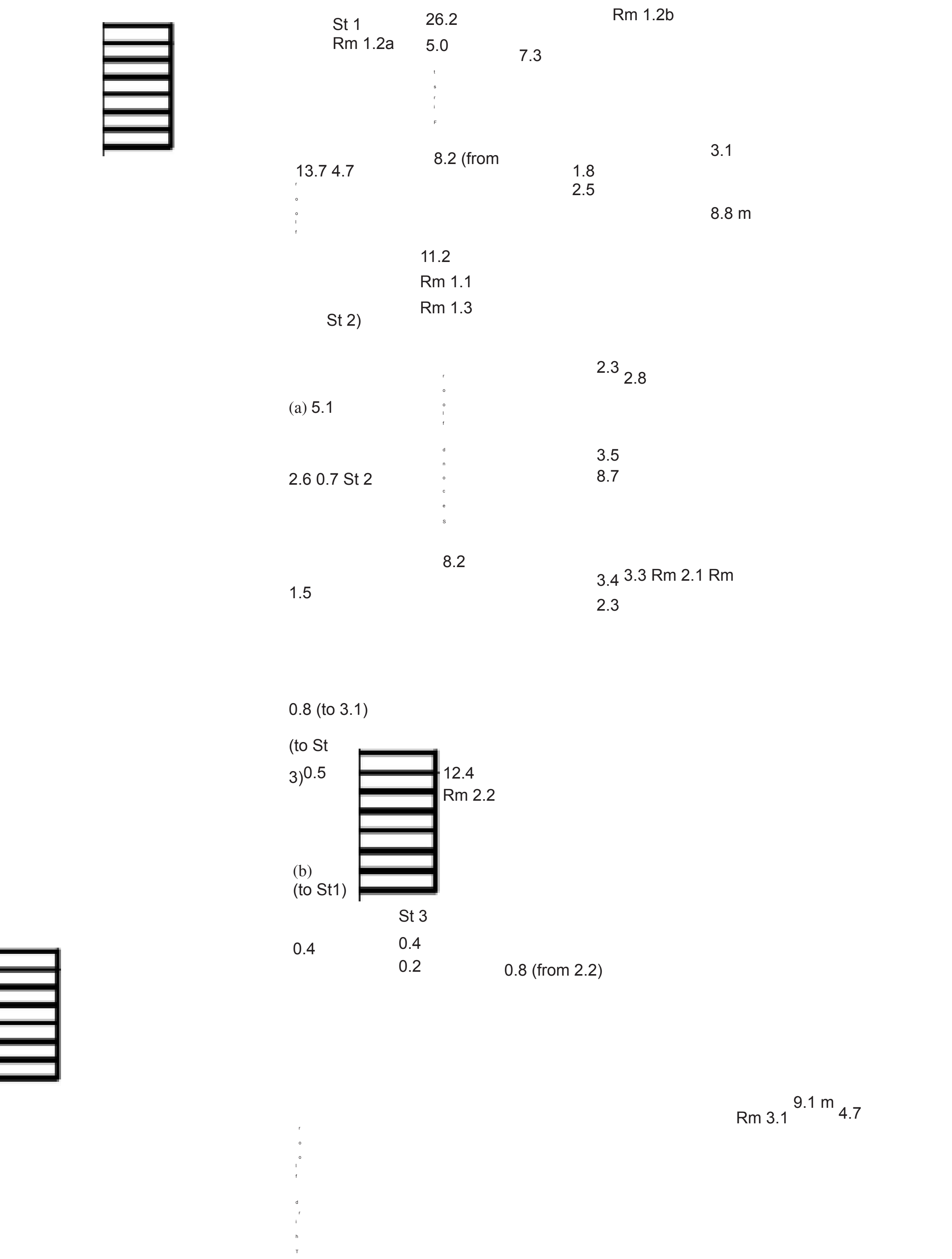
We evaluate the performance of a system of sensors in terms of how accurately and quickly the system estimates the contaminant release conditions such as the release location and mass. In practice, different performance criteria may be set depending on the objectives of the particular monitoring system.

3. Case study: sudden tracer release in a three-story building

This section explores the potential utility of the two-stage Bayesian interpretation algorithm for designing a sensor system that consists of single level threshold sensors. Several examples are con structed using data from a single case study. The objectives are: (1) to test how well Bayesian interpretation works with threshold sensors; and (2) to explore how the system's performance varies with the sensor threshold level, response time, and error. The emphasis here is not on optimizing the Bayesian algorithm for this case study, but to demonstrate how a Bayesian methodology can be used to assess sensor characteristics for any sensor type, such as single-level threshold sensors. Actual implementation for a specific sensor system may require further refinement of the algorithm.

3.1. Building characterization, data collection, and model generation

The study focuses on one unit in a multiunit building located at the Dugway Proving Grounds, Utah (Sextro et al., 1999). The unit consists of 660 m^3 of interior volume and approximately 280 m^2 of floor area on three levels (see Fig. 1). A mechanical air-handling unit (AHU) supplies air to the first and second floors, and its return is on the first floor. The AHU is a 100% recirculating unit (i.e., there is no deliberate outside air intake). Air exchange between inside and outside occurs by means of pressure-driven airflow through leaks in the unit's envelope. Airflow between interior zones occurs by means of mechanically induced flow through the system ducts, by pressure-driven or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(b)
(to St1)
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0.2
0.8 (from 2.2)
Rm 3.1
9.1 m
4.7

5.1 (from St 2)

0.4 0.7 4.9

(c)

Fig. 1. Case-study unit at the Dugway Proving Grounds, Utah. Plan views of: (a) floor 1 (ground level); (b) floor 2; (c) floor 3. Selected intrazonal and AHU airflow rates for the actual release (as calculated by COMIS at the first time step) are shown, in units of $m^3 min^{-1}$.

convective airflow through open doorways, and by pressure-driven airflow through interior leakage paths.

Sextro et al. (1999) conducted fan pressurization tests to determine the leakage characteristics of the building. They also conducted 12 tracer-gas experiments. In each, approximately 20 g of propylene was instantaneously released at a specific interior location, and the concentrations in each room and the staircase were recorded every 20 s.

For our study, we selected the data from one tracer-gas experiment (Trial 1). In this case, the release occurred outside the return grill of Room 1.2a (first floor). The AHU was operating and all

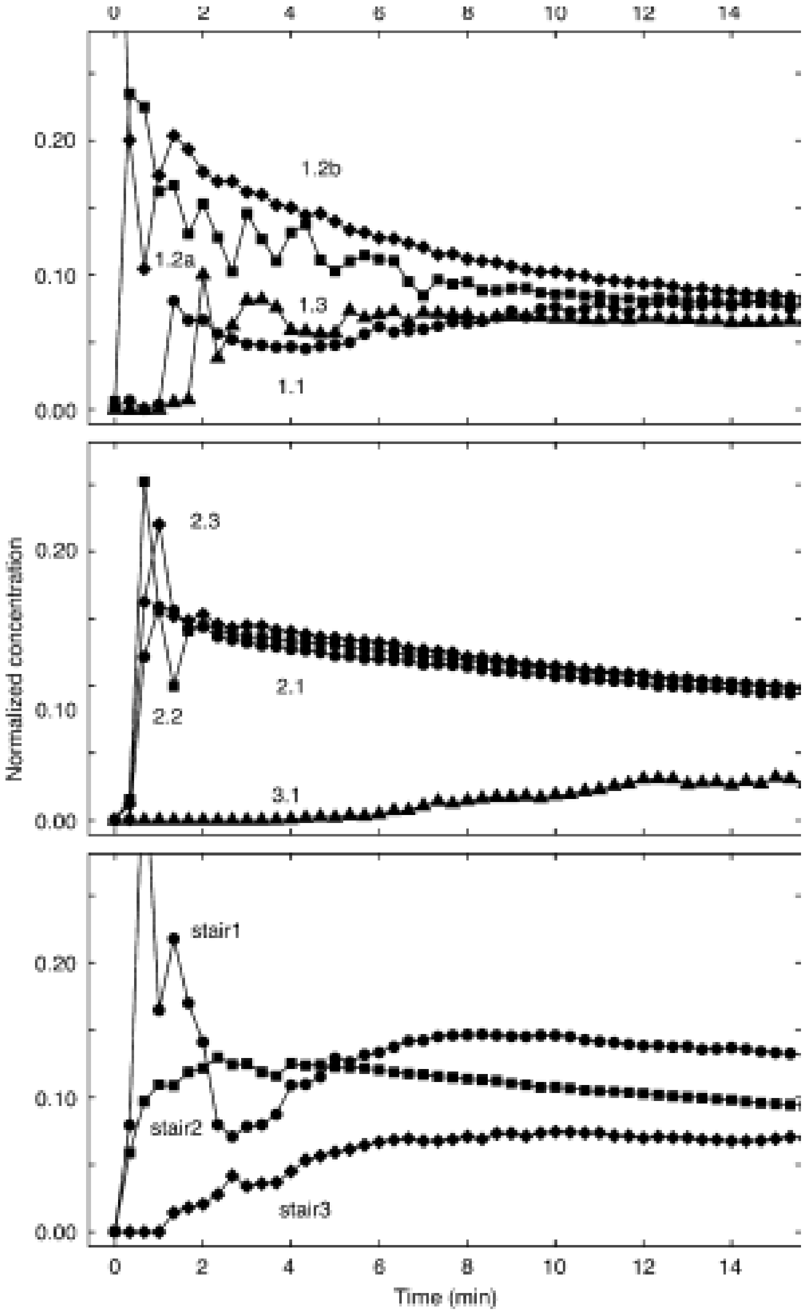


Fig. 2. Time-dependent tracer gas concentrations for case-study release normalized by theoretical peak concentration in the experiment: (a) first floor rooms; (b) second floor and third floor rooms; (c) staircases.

interior doors were open. Fig. 2 displays concentra tion data collected from the sensors.

Using the building leakage characteristics ob tained from fan-pressurization tests, Sextro et al. (1999) developed a multizone airflow and pollutant dispersion model for the unit using COMIS (Feustel, 1999). COMIS predicts airflow induced by wind, thermal buoyancy, and mechanical venti lation by representing the building as a collection of well-mixed zones connected by flow paths such as cracks, doors and windows, and ductwork. Air is assumed to be incompressible and airflow through these pathways is predicted by imposing mass balance and calculating pressure differences among the zones.

A library of 5000 simulated contaminant releases was generated using this model, by sampling from statistical distributions of a set of key input parameters, as described by Sohn et al. (2002b). The variable input parameters are summarized in Table 1.

3.2. Hypothetical threshold sensor data

We generated hypothetical threshold sensor data by interpreting the tracer data from the experiment as if they were concentrations to which surface acoustic wave (SAW) sensors were exposed. SAW sensors are piezoelectric devices, often configured to provide alarms based on whether the incoming concentrations are above or below a predefined trigger or threshold level. False positive and false negative alarms may occur, according to the performance characteristics of each sensor, or the inability of the sensor to distinguish between the contaminant of interest and interfering chemi cals that also may be present in the air.

Table 1
Assumptions used to generate the library of 5000 simulated contaminant releases

Parameter	Values
Source location	Ten locations: any room plus stairwell. Each location is equally probable
Source duration	1 s to 5 min; log-uniform distribution
Source amount	10–100 g; log-uniform distribution
Door position	Three scenarios: (1) all interior doors open; (2) all interior doors closed; (3) doors between staircase landings and adjacent rooms closed, all others open

We generated hypothetical alarm data for sensors with different performance characteristics, based on discussions with several developers and users of SAW sensors. Three sensor attributes were varied: threshold level, response time, and error.

The threshold levels were chosen relative to the measured concentrations during the first 120 min of the release event. The lowest selected threshold would cause 98% of the data to trigger the alarm, while the highest threshold would trigger an alarm for only 1% of the data. However, for presentation purposes, we normalize both threshold levels and concentration data by the concentration that would be found in the release zone if the entire release amount instantaneously mixed throughout that zone. That is, thresholds and concentrations are reported in terms of the theoretical maximum peak concentration that could be measured in the system under the perfectly well-mixed assumption. With this normalization, the lowest threshold level was 0.02% of the maximum peak, and the highest was 16%.

Sensor response times ranged from 20 to 180 sec. In the simulations, concentrations are averaged over the response time, and then compared to the appropriate threshold level. Note that averaging over the response time corresponds to an assump tion that the SAW desorption cycle is brief relative to its adsorption cycle. In our simulations we ignored the duration of the desorption cycle (i.e., each sensor started integrating the next cycle of data as soon as it reported an alarm or no-alarm condition).

Simulations were run using data with and without synthetically added error. For simulations with added error, we generated sensor signals according to the following assumptions: (1) if the actual concentrations are within 25% of the sensor thresh old level, the signal will be false 50% of the time; and (2) for concentrations outside of this range, the signal will be false either 10% or 30% of the time, depending on the assumed sensor error.

In this implementation of Bayes' rule, the like lihood function is based on the probability used to generate the false positives and negatives. For example, for data generated with a 30% error, the likelihood is 0.3 when the modeled concentration is more than 25% above the threshold level and the sensor has not signaled on; conversely, the like lihood is 0.7 if the sensor has signaled on. For the simulations using data without synthetically added error, we assume 5% error for all data. We did not

assign 100% confidence to this data because of inherent uncertainty and variability. In practice, the designer of the sensor system should have reliable information on the sensor's actual rate of false positives and false negatives.

Fig. 3 illustrates the conversion of measured concentration data to simulate threshold data. Fig. 3(a) shows normalized time-averaged concen tration data, with the threshold level indicated.

Fig. 3(b) shows the threshold data that would result from a threshold sensor with no error and instantaneous response. Here, "1" signals that the concentration exceeds the threshold. Fig. 3(c) shows the threshold data, corrupted with false negatives or positives. Because the false readings are generated stochastically, different realizations of the data in Fig. 3(c) would exhibit different patterns of output signals.

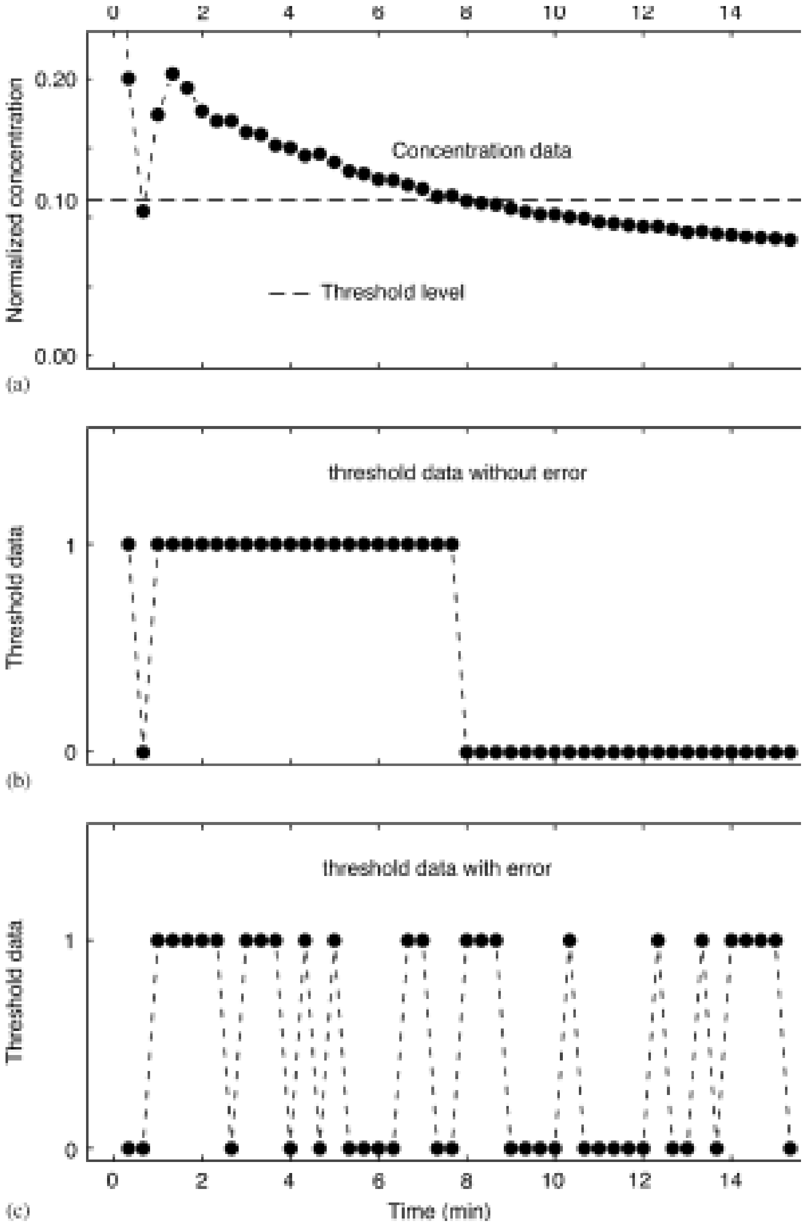
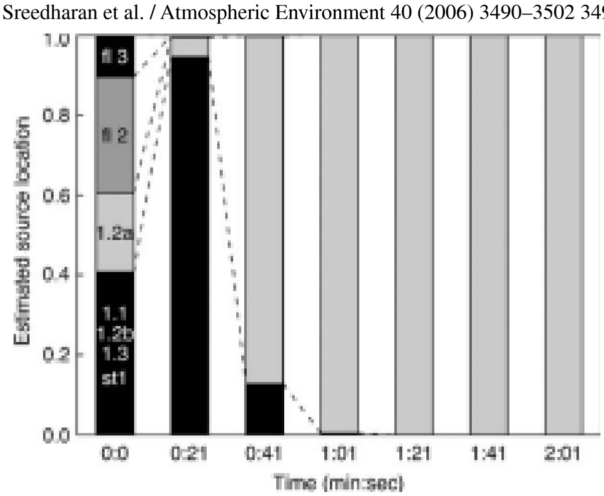


Fig. 3. Sample illustrating conversion of tracer gas concentration to threshold data: (a) concentration data; (b) threshold data without simulated error added; (c) threshold data with simulated error added.

For the case-study examples, we systematically varied the sensor characteristics, as described above. In cases where error was specifically investigated, for each sensor attribute, we generated 50 sets of error-added threshold data, analogous to those displayed in Fig. 3(c), for each sensor in the system. Each combination of threshold level, response time, and error produced a data stream against which to



apply the Bayes Monte Carlo algorithm. The algorithm was used to determine the release location and release magnitude; the time of release was assumed known.

4. Results and discussion

To demonstrate data interpretation using threshold sensor data, we first investigate the ability of the sensor system to estimate the release location, mass, and duration. Next, we investigate the effect of changing the threshold level and response time characteristics, and lastly, the effect of changing the sensor error in conjunction with these characteristics.

4.1. Estimating release characteristics with threshold data

The information content in threshold sensor data is significantly less than that in direct concentration measurements. Nevertheless, the sensor system can successfully reconstruct the source, at least in some circumstances. We demonstrate this with an exam ple in which the concentration data have been converted to threshold data using a threshold level of 2.3%, a sensor response time of 20 s, and without added error. We judge the sensor system perfor mance by its ability to reduce the uncertainty in the estimates of the release location, mass, and duration parameters, and by the time required to do so.

Fig. 4 depicts the time required to identify the release location (Room 1.2a). At time zero, every zone is assumed to be equally likely as the release location. As sensor data arrive, the Bayes algorithm adjusts these probabilities, identifying the release location with greater than 90% confidence within 1 min. If rapid response hinges on locating a source very quickly, this example suggests that threshold sensors under this network configuration and data quality may be acceptable for real-time monitoring. Fig. 5 shows the time-resolved estimates of the release mass and duration parameters. These para meters are accurately estimated within tight un certainty limits after 10 min.

Fig. 4. Probability of source being in location indicated, as estimated with the Bayes Monte Carlo algorithm using threshold data with response time of 20 s, threshold level of 2.3%, and without added error. The actual release location is Room 1.2a. Time is referenced to the instantaneous release event.

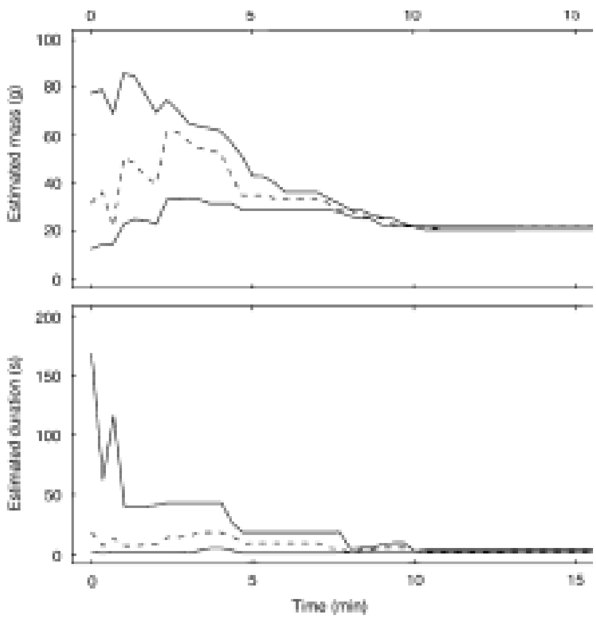


Fig. 5. Release mass and release duration estimated with the Bayes Monte Carlo algorithm using threshold data with response time of 20 s, threshold level of 2.3%, and without added error. The solid lines indicate 80% confidence intervals; dashed lines indicate medians. (Actual release mass was 20 g, and released as a puff.)

4.2. Effects of sensor threshold level and response time

Here, we explore tradeoffs between sensor thresh old level and response time. The threshold level was

varied between 0.02% and 16% of the theoretical peak concentration, and the response time was varied between 20 and 180 s. No added error was included in these data sets, to isolate the effects of threshold level and response time. Fig. 6 shows the time required to identify the correct release location with 90% confidence for these cases. The lowest threshold levels (0.02% and 0.23%) and highest threshold levels (14% and 16%) are often unable to identify the release location because they yield data that varies little among zones. Fig. 6 also shows that for the intermediate threshold levels there is little difference in the time required to locate the source, particularly for sensor response times between 20 and 120 sec.

Fig. 7 shows estimates of the release amount for four combinations of response times (60 and 120 s) and threshold levels (2.3% and 9%). With higher threshold level sensors, the algorithm estimates the release mass to a higher level of confidence more quickly. The sensor system with the high-threshold level sensors reduces the posterior probabilities of many more realizations than the sensor system with the low-threshold level sensors. Therefore, the calculated parameter uncertainty bounds for release mass are narrower. We observed this relationship consistently across all response times and thresholds between 2.3% and 11%.

Over the range of conditions shown in Fig. 7, the effect on the results of sensor response time is weaker. As the response time increases, the sensor system receives information less frequently, and the confidence intervals broaden somewhat. In compar ing Figs. 6 and 7, we observe that more time is needed to estimate with high confidence the release mass than the release location.

Summarizing the results depicted in Figs. 6 and 7, the performance of the sensor system depends significantly on threshold levels relative to actual concentrations, and less on response time. If airborne concentrations in the actual building can vary over a broad range, a sensor system with

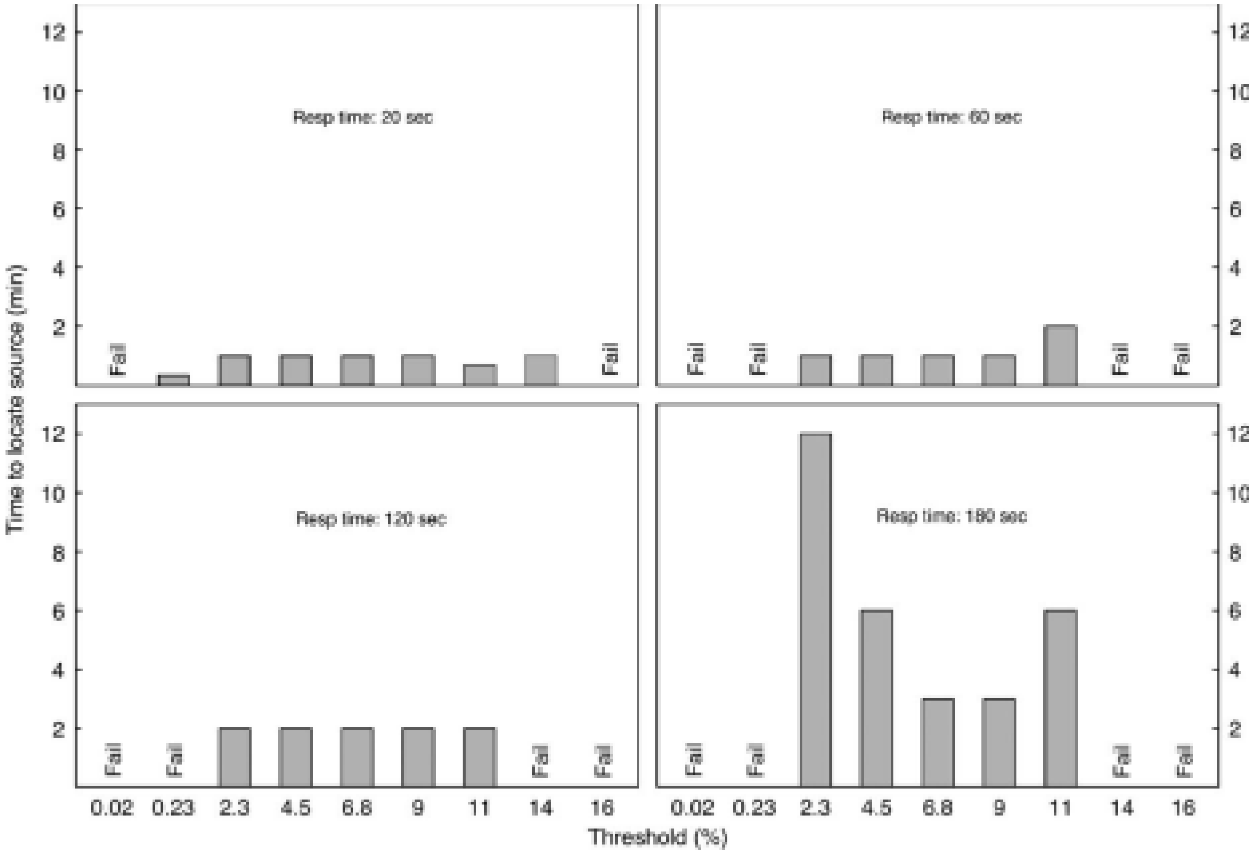


Fig. 6. Time required to locate the release location, as a function of threshold level and sensor response time, using threshold data with no added error.

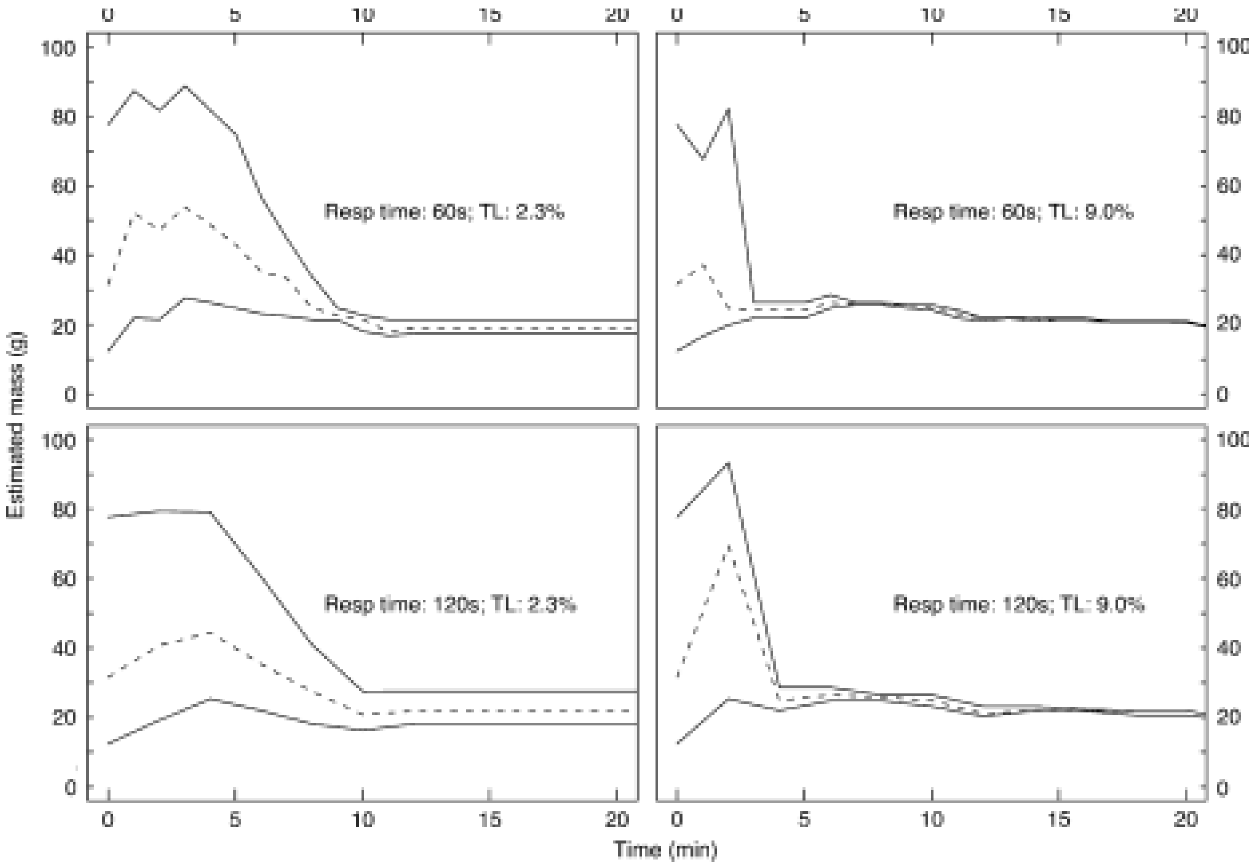


Fig. 7. Estimated mass released as a function of threshold level (TL) and sensor response time, using data without added error; median (dashed line), and 10th and 90th percentiles (solid lines).

multithreshold sensors should be tested since they may better cover the range of airborne concentra tions.

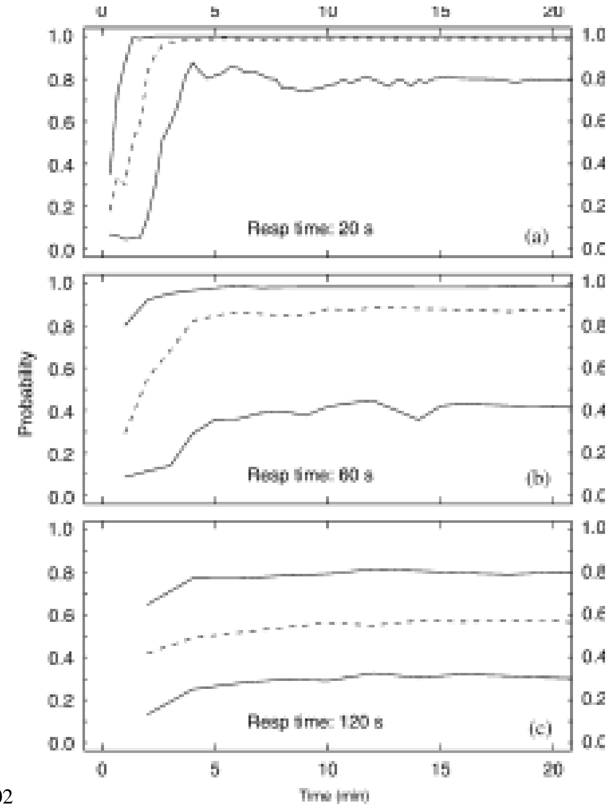
4.3. Effects of sensor error

In this example, we include error in the threshold sensors. As expected, the algorithm requires more time (and thus data) to identify the source zone with high confidence.

Fig. 8 shows the time required to locate the release location for the case of fixed sensor response time (20 s) and error (30%), but with varying threshold level. Each of the three cases is based on 50 data realizations with randomized error. Each frame in the figure shows the time-dependent probability of correctly identifying the release location. Even with relatively high error, the sensor system containing sensors with low- and medium threshold levels rapidly identifies the source location with high probability in most realizations. The sensor system with medium-threshold sensors per forms best under these conditions, demonstrating the ability to locate the source with 90% confidence more rapidly in most cases than the low-threshold level.

The medium-threshold sensor performs better than the low-threshold sensor for two likely reasons. (1) A higher threshold level reduces the posterior probabilities of a larger subset of model realizations than the lower threshold level. (2) While a low threshold sensor receives signaling-on information before the medium-threshold sensor, a medium threshold sensor receives the signaling-off informa tion sooner. If both signaling-on and signaling-off information is important for data interpretation, the sensor system based on medium-threshold sensors may provide more overall information, more rapidly.

In contrast to the sensor system with low- and medium-threshold sensors, the sensor system with high threshold sensors requires significantly more data to estimate the release location with high



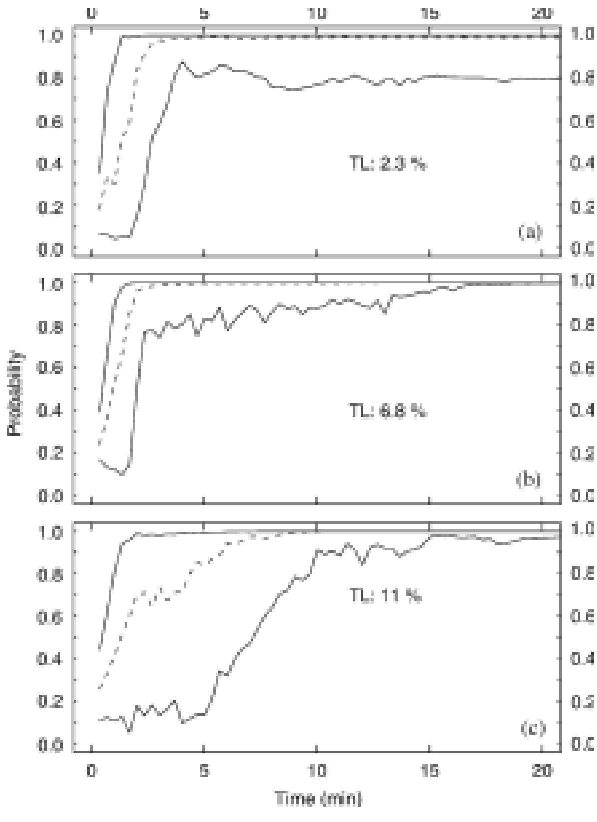


Fig. 8. Probability of correctly identifying the release location using threshold data generated with 30% error, variable thresh old level (TL), and fixed response time (20 s); median (dashed line), 10th and 90th percentiles (solid lines) for 50 data realizations. Threshold level:

(a) 2.3%, (b) 6.8%, (c) 11%.

90th percentiles (solid lines) for 50 data realizations. Sensor response time: (a) 20 s, (b) 60 s, (c) 120 s.

confidence, for a majority of the data realizations (see Fig. 8(c)). Furthermore, the wide confidence intervals in Fig. 8(c) prior to 7 min are caused by inconclusive or incorrect estimates of the release location for several data realizations.

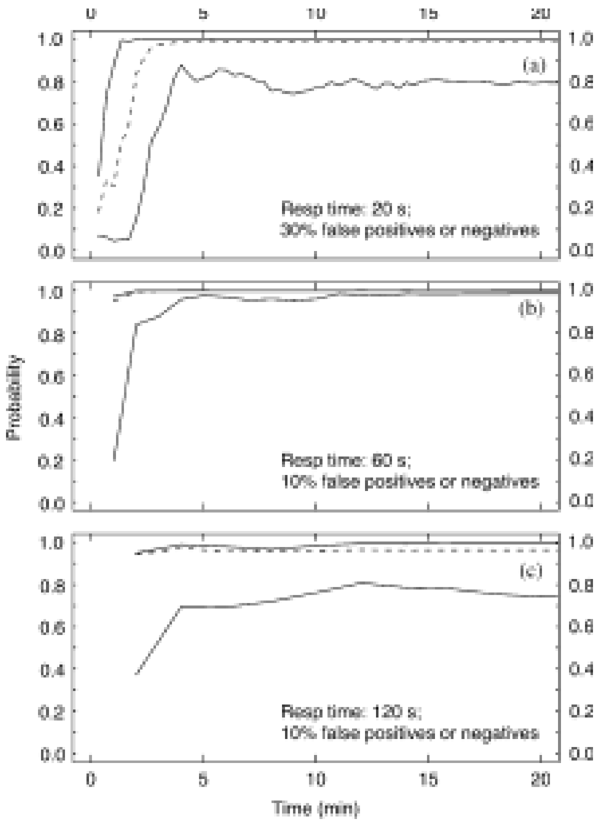
The results obtained by investigating data without adding simulated error (i.e., false positives and negatives) suggest that certain parameters are more easily estimated than others; namely, the release location was estimated more easily than the release mass. The sensor system must, thus, be designed to meet the performance objectives of the overall system, given the many possible goals of a monitor ing system. For example, accurate predictions of evolving concentrations may rely on accurate estimates of both release location and mass.

Fig. 9 shows how the time required to identify the release location varies with sensor response time. In these simulations, we used sensors with a 2.3% threshold level and 30% error. As the response time

Fig. 9. Probability of correctly identifying the release location using threshold data generated with 30% error, variable sensor response time, and threshold level of 2.3%; median (dashed line), 10th and

increases from 20 to 120 s, the ability of the system to estimate the release location and mass degrades. These results are similar to those discussed in Section 4.2. For sensors with a fixed threshold level, a longer response time reduces the amount of information, and, therefore, reduces the certainty with which release parameters can be estimated.

To investigate tradeoffs between sensor speed and accuracy, we compare system performance with more rapid, but less accurate sensors against system performance with slower but more accurate sensors (Fig. 10). System 1 consists of sensors with a 20-s response time and 30% error (Fig. 10(a)); System 2 consists of sensors with a 60-s response time and 10% error (Fig. 10(b)); and System 3 consists of sensors with a 120-s response time and 10% error (Fig. 10(c)). All three systems utilize sensors with a threshold level of 2.3%. System 1 receives data at a higher rate, but lower accuracy than do the other systems. System 2 receives data at a higher rate than



pants in the event of high-risk pollutant releases.

The premise of this paper is that the selection of sensor characteristics is best performed from a systems perspective. Here, we have demonstrated—albeit for a limited set of circumstances—that a network of single-level threshold sensors can be used to determine the location and magnitude of the release within a Bayes Monte Carlo framework. More importantly, treating the network as a system may lead to better choices for sensor characteristics like response time and error, than might be the case when considering sensors individually.

The actual rate of false readings (i.e., false positives or negatives) for real sensors is likely to be less than 30%. Probabilistic results reached by the Bayesian algorithm based on the assigned confidence are therefore likely to be conservative.

A primary purpose of this work is to illustrate the relationship between sensor characteristics and sensor system performance. The work also shows that the two-stage Bayesian Monte Carlo algorithm is a promising approach for designing sensor systems, even when using threshold-type sensors.

Important questions remain for future investiga tion. How well does the algorithm work against a full array of release conditions, including slow,

Fig. 10. Probability of correctly identifying release location using sensors with varying sensor response time and error, with threshold level of 2.3%; median (dashed line), 10th and 90th percentiles (solid lines) for 50 data realizations. (a) Response time 20 s, error 30%; (b) response time 60 s, error 10%; and (c) response time 120 s, error 10%.

System 3, but with the same accuracy. We observe that System 2 clearly outperforms the other two systems, and System 3 performs slightly better than System 1. Therefore, in this example, a sensor system that is based on slower but more accurate sensors identifies the release location with higher confidence, more quickly, than a sensor system using faster, but less accurate, sensors. This result was consistently observed in our simulations across most threshold levels, suggesting that slower, but more accurate threshold sensors may be more informative and lead to faster definitive interpreta tion than rapid, less accurate, threshold sensors when deployed in a building-monitoring system.

5. Conclusion

Real-time environmental monitoring systems have the potential to help protect building occu

steady releases? How should the library of simula tions be generated so as to simultaneously ensure sufficiently dense sampling of the space of input variables, and complete coverage of possible release conditions? What information from other types of sensors could improve the overall performance and cost-effectiveness of the sensor system? How can the information generated from this type of monitoring system be used to specify responses that protect building occupants and first responders?

The deployment of a monitoring system of the type explored in this paper is likely to occur first in buildings that are much larger and more complex than the one considered here. The scalability of the Bayes Monte Carlo algorithm to larger and more complex systems poses unexplored challenges. With more complex buildings, system characterization is technically more challenging, and also more ex pensive. Hybrid methods that augment prior knowl edge with sensor system data that monitors building operations to learn about airflows and contaminant transport may improve overall system performance. Such advances would not only be beneficial for designing indoor monitoring systems, but may potentially be extended to help diagnose and interpret data from large-scale contaminant releases

to the ambient atmosphere and to other environ mental media. Such approaches also hold the promise of facilitating improvements in building performance with respect to energy use, thermal comfort, and indoor air quality.

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